

Article

Energy-Aware Digital Twin Frameworks for Port Building Clusters: Integrating Structural Health Monitoring, Smart Metering, and Retrofit Prioritization

Rossella Roversi ^{1,*} , Fabrizio Cumo ², Elisa Pennacchia ³ , Virginia Adele Tiburcio ²  and Claudia Zylka ³ 

¹ Department of Architecture, University of Bologna, Viale Risorgimento, 2, 40136 Bologna, Italy

² Department of Planning, Design, Technology of Architecture, Sapienza University of Rome, Via Flaminia, 72, 00196 Rome, Italy; fabrizio.cumo@uniroma1.it (F.C.); virginiaadele.tiburcio@uniroma1.it (V.A.T.)

³ CITERA Interdepartmental Research Centre Territory, Building, Restoration and Environment, Sapienza University of Rome, Via A. Gramsci, 53, 00197 Rome, Italy; elisa.pennacchia@uniroma1.it (E.P.); claudia.zylka@uniroma1.it (C.Z.)

* Correspondence: rossella.roversi@unibo.it

Abstract

Ports combine clusters of operational buildings, shared energy infrastructure, and structurally critical assets requiring coordinated management to ensure safety and efficiency. Nevertheless, existing Digital Twin (DT) frameworks for building energy management rarely integrate Structural Health Monitoring (SHM) with energy performance assessment, while port-specific implementations remain scarce. This paper presents a pre-operational energy-aware DT architecture for port building clusters, structured in a unified five-layer framework integrating three capabilities: (i) EGMS/InSAR-based SHM screening with planned in situ sensing and computer-vision inspection workflows; (ii) smart metering and measurement and verification (M&V) protocols aligned with ISO 50001/50015 and IPMVP standards; and (iii) weighted multi-criteria prioritization considering structural condition, energy saving potential, service continuity, and cost. The framework is applied to the Port of Formia (Italy), a brownfield district comprising nine buildings (3371 m²), 16 high-mast lighting towers, shore power infrastructure, and 90 kWp of planned photovoltaics. In the absence of operational metering, energy and carbon values are reported as bounded ex-ante scenario estimates, not as verified performance outcomes. The analysis estimates photovoltaic generation of 116–137 MWh/year and lighting retrofit savings of 31.5–36.8 MWh/year; the related carbon values are treated as gross grid-displacement upper bounds pending measured self-consumption and export data. A four-phase validation roadmap with quantitative acceptance criteria supports the transition from feasibility assessment to verified performance.

Keywords: digital twin; port buildings; energy retrofit; structural health monitoring; smart metering; BIM-IoT integration; measurement and verification



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1. Introduction

1.1. Background and Motivation

Maritime transport and the management of port built environments are currently subject to increasingly stringent regulatory and strategic pressures aimed at substantially reducing carbon emissions and improving overall sustainability [1,2]. European directives such as the Energy Performance of Buildings Directive (EPBD) [3], FuelEU Maritime [4],

and the Alternative Fuels Infrastructure Regulation (AFIR) [5] impose progressively demanding requirements concerning energy efficiency, electrification of port operations, and integration of renewable energy sources, applying to both vessels and port-side buildings and shared energy services. These obligations align closely with national energy transition pathways, particularly those defined for Italy [6]. At the same time, ensuring the operational continuity and long-term reliability of critical port infrastructure (including berths, piers, and lighting towers) requires the adoption of preventive structural monitoring systems and advanced data-driven predictive approaches [7]. In this context, ports represent a particularly relevant testbed for integrating energy management with structural reliability. They encompass a heterogeneous mix of assets, ranging from operational buildings (offices, warehouses, fish markets, and restaurants) to public utility infrastructure (external lighting systems, shore power supplies for vessels, and electrical distribution networks) and high-criticality civil structures (berths and piers) that are continuously exposed to challenging marine conditions, such as subsidence, erosion, and seismic activity [8]. Consequently, the operational challenge is inherently twofold: first, to accurately measure, monitor, and reduce energy consumption together with the associated carbon emissions; and second, to proactively assess the structural health of infrastructure components in order to prevent catastrophic failures that could severely disrupt port operations and compromise overall system resilience [9,10]. These two imperatives converge when examining the full lifecycle of constructed port infrastructure. While most buildings, technical systems, and shared services are already in the Operation and Maintenance (O&M) phase, major energy efficiency interventions, such as photovoltaic installations, lighting retrofits, and shore power electrification, are typically still in the design or pre-commissioning stage [11]. In the present work, this transitional period is defined as the pre-operational feasibility assessment phase. During this window, existing documentary assets, including maintenance plans, architectural and topographic surveys, design specifications, and satellite monitoring data, constitute a readily available information base. From this foundation, a coherent decision-making framework can be developed prior to the deployment of comprehensive real-time measurement infrastructure, thereby enabling informed prioritization of interventions while minimizing initial investment risks [12].

1.2. State of the Art and Research Gap

The Digital Twin (DT), understood as a dynamic digital replica that continuously integrates data from the physical world with informational models across the operational lifecycle [13], is progressively being adopted as a supporting platform for operations and maintenance in complex infrastructure contexts [14,15]. In the built environment, DT applications have achieved greater maturity in the operational phase, largely due to the widespread availability of sensors, building automation systems (BAS/BMS), and cloud/edge computing platforms [16,17]. Recent literature reviews on building energy management [16] and energy-oriented DT applications [17], together with studies on post-construction DT approaches [18] and urban digital-twin roadmaps [19], consistently highlight the potential of these systems for real-time monitoring, predictive analytics, fault detection and diagnosis (FDD), and scenario-based evaluation of energy efficiency interventions. Despite these advances, several persistent challenges continue to limit the operational utility of energy-aware DTs. These include the effective integration of highly heterogeneous data sources (satellite observations, point sensors, distributed energy metering, and maintenance metadata), which demands robust acquisition pipelines capable of normalizing disparate formats, sampling frequencies, and data quality levels. A further issue concerns interoperability: although the Industry Foundation Classes (IFC) standard (ISO 16739) [20] offers a solid schema for geometry and static asset attributes

within Building Information Modeling (BIM), the seamless linkage between static BIM models and dynamic IoT telemetries remains problematic without additional semantic layers. To address this limitation, international communities have proposed open ontologies such as Brick [21,22], designed for the representation of sensors, assets, and their relationships, and Project Haystack [23] for automation and facility management data. The Brick ontology, in particular, enables portable semantic mapping between physical assets (e.g., “South_Pier_Lighting_Zone”) and associated measurements (kW, lux, occupancy), thereby reducing the cost of ad hoc integrations and promoting cross-site application portability for Key Performance Indicators (KPIs) and FDD [14]. Additional critical issues involve data governance, quality assurance, temporal synchronization, and cybersecurity in operational technology (OT/ICS) environments. Perhaps most relevant for energy-focused DTs is the limited adoption of consolidated standards for the rigorous quantification of energy benefits. Without well-defined baselines, Energy Performance Indicators (EnPIs), and Measurement and Verification (M&V) protocols, DT implementations risk remaining primarily descriptive visualization tools rather than truly predictive and prescriptive platforms. Standards such as ISO 50001 (Energy Management Systems) [24] and ISO 50015 (Energy Data and Information Management) [25] provide structured principles for systematic energy data handling, baseline definition, EnPI development, and continuous improvement through the PDCA cycle. Complementarily, the International Performance Measurement and Verification Protocol (IPMVP) [26] delineates four operational options (A–D) for the reliable determination of energy savings resulting from retrofits or operational optimizations. The integration of these standards into DT architectures is therefore essential if such systems are to move beyond monitoring toward verifiable energy optimization.

A progressive convergence is observed in the broader literature between three-dimensional modeling, distributed sensing (both structural and energy), predictive analytics, and scenario simulation of efficiency measures [27,28]. The main DT approaches in the built environment are compared in Table 1.

Table 1. Comparison of DT approaches in the built environment. Energy maturity is maximized when smart metering is present and M&V conforms to standards. Energy maturity for the hybrid SHM approach is rated Medium when considered in isolation; the integrated framework proposed in this study elevates it to High through the addition of ISO 50001/IPMVP-compliant smart metering and M&V governance.

Approach	M&V Integration	Energy Maturity	Interoperability	Scope
BIM + proprietary BMS	None	Medium (FDD, trend analysis)	Low (XML/custom API)	Static asset + LV automation
Multi-source DT with Brick/Haystack	High (IPMVP-ready)	High (baseline, EnPI)	High (RDF/JSON-LD)	IFC + IoT + metadata
DT with hybrid SHM (InSAR + sensors + vision)	High if an M&V plan is defined	Medium (standalone)/High (this study)	Medium-high (GIS + semantics)	Geometry + deformations + anomalies

However, in the specific domain of ports, these limitations are even more pronounced. Existing implementations remain frequently sectoral and fragmented, addressing either logistics and operational processes or isolated energy aspects, with only limited cross-domain integration [15–29]. Key gaps include the insufficient incorporation of Structural Health Monitoring (SHM) data, such as deformations, anomalies, and fatigue, into energy performance models, despite the evident bidirectional influence of structural integrity on operational energy efficiency (for example, settlements in quay walls or pavements that may increase energy losses in cranes or lighting systems) [8]. Further limitations concern the underdeveloped semantic standards for unified asset identification across structural

and energy domains, and the still-emerging nature of truly hybrid SHM-energy approaches. Although technological convergence is advancing, its practical application in port environments remains incomplete, particularly with respect to modeling the interdependencies between infrastructure condition and energy consumption [30,31]. Consequently, the development of an energy-aware port DT that systematically couples structural reliability with energy optimization constitutes a concrete scientific and operational challenge requiring a multidisciplinary response.

In port environments, the physical condition of assets and their energy performance are not independent domains; rather, they are strongly coupled throughout the infrastructure lifecycle. Structural issues such as foundation subsidence can undermine the long-term reliability of photovoltaic installations, while detected anomalies in a beacon tower necessitate consolidation works before any LED lighting retrofit can be safely implemented. Similarly, a pier exhibiting uncharacterized vertical movements cannot be confidently included in a shore power electrification plan. A prioritization framework that treats structural monitoring and energy optimization as separate processes therefore risks generating technically incoherent retrofit decisions.

1.3. Research Objectives

To overcome this limitation, the present study adopts a hybrid monitoring approach in which SHM and energy performance are integrated as interdependent components feeding into the same decision-making pipeline. On the structural side, the framework combines three complementary observation scales:

1. Satellite-based European Ground Motion Service (EGMS) data derived from multi-temporal InSAR (Sentinel-1), which provides millimetric measurements of vertical and horizontal ground motion with regular updates and is particularly useful for regional-scale subsidence monitoring and risk zoning [32];
2. In situ high-frequency sensors (accelerometers, inclinometers, and crack gauges) for local validation and rapid dynamic phenomena;
3. Computer vision techniques supported by deep learning for scalable anomaly and crack detection from images acquired via drones or fixed cameras [33]. The fusion of these sources reduces false alarms and increases diagnostic reliability, with established validation practices such as InSAR + GNSS/sensor integration [34]. Importantly, the immediate availability of open EGMS data makes this hybrid SHM approach especially valuable during the pre-operational feasibility assessment phase, allowing structural screening to begin even before full IoT infrastructure is deployed.

On the energy side, once structural feasibility is established, governance shifts from simple meter reading to active performance management. This transition relies on ISO 50001 for the procedural PDCA-based Energy Management System, ISO 50015 for data quality, traceability and synchronization [24,25], and the IPMVP protocol, whose Option C (whole-facility metering with regression adjustments) is often the most practical choice for port retrofits involving lighting and photovoltaic systems, offering accuracies typically in the range of $\pm 10\text{--}15\%$ [26]. In many Italian ports, external lighting alone can account for approximately two-thirds of total electrical demand [28–36], representing a high-impact leverage point. Opportunities include LED retrofits combined with adaptive controls (dusk-to-dawn and occupancy-based), which can achieve 50–70% energy reductions compared to legacy systems [36,37], supported by smart sub-metering for both benefit verification and predictive maintenance through harmonic and power-factor analysis [38].

The research gap addressed by this work lies precisely at the intersection of three converging but still poorly integrated bodies of literature: energy-oriented DTs for buildings, hybrid SHM for critical infrastructure, and standardized energy governance under M&V

protocols. While individual studies have explored energy DT applications [17], zero-energy port concepts [28], or smart lighting control in ports [36], no existing framework proposes an operational workflow for brownfield ports that jointly combines multi-scale SHM screening, ISO/IPMVP-compliant energy governance, an explicit evidence taxonomy (distinguishing document-derived, estimated, and to-be-validated results), and multi-criteria prioritization within a single pre-operational feasibility assessment pipeline. Table 2 positions the present contribution relative to the most relevant literature, highlighting how this study adds a structurally informed decision layer that previous works have not fully addressed.

Table 2. Comparative positioning of the manuscript against the most relevant DT and low-carbon port literature.

Main Gap Addressed Here	SHM Integrated	Port Context	Energy/Retrofit Focus	Scale	Study
Maps energy DT applications, but no port-specific or SHM-coupled workflow.	No	No	High	Review	do Amaral et al. [17]
Strong DT + AI energy logic, but not port services or structurally informed prioritization.	No	No	High	Building/CPS	Agostinelli et al. [27]
Zero-energy port-area orientation, but no hybrid SHM-energy screening and no explicit evidence taxonomy.	No	Yes	High	Port area	Agostinelli et al. [28]
Smart control for port lighting, not a full DT and not an M&V-oriented asset workflow.	No	Yes	Service-specific	Port lighting	Sifakis et al. [36]
Integrates SHM, building clusters, uncertainty-aware ex ante results, M&V protocol and hybrid prioritization.	Yes	Yes	High	Port buildings + shared services	This study

Building upon the identified gaps, the present study investigates the following primary research question: To what extent can a pre-operational DT architecture (combining BIM, IoT-ready data pipelines, and AI-enabled analytics to be validated after deployment), applied to a real port case study, support concurrent screening of structural condition and energy performance while prioritizing maintenance and retrofit interventions toward low-carbon and net-zero objectives [39]?

To address this question, the study pursues five specific objectives:

1. To define a unified DT architecture that coherently integrates multi-source structural monitoring (SHM) with energy monitoring systems compliant with relevant ISO standards (50001, 50015, and 16739);
2. To design a comprehensive data acquisition and semantic data management solution capable of handling heterogeneous sources, including EGMS/InSAR satellite data, in situ sensors, smart metering, PV inverters, and existing documentary records;
3. To establish a multi-domain set of KPIs, covering structural, energy, carbon, operational, and economic dimensions, together with calculation methodologies consistent with M&V standards (IPMVP and ISO 50015);
4. To develop a multi-criteria decision support layer for intervention prioritization that incorporates structural risk assessment, energy and carbon benefits, service levels, and economic feasibility;

5. to validate the technical and operational feasibility of the proposed framework on the Port of Formia case study, while transparently distinguishing between KPIs derived directly from available documents, engineering estimates anchored in project data and literature, and parameters requiring post-implementation validation.

The contributions of this work are twofold:

1. This study introduces a comprehensive, energy-aware DT framework tailored to the specific needs of existing (brownfield) port districts. The proposed framework is built upon five interconnected layers, starting from the BIM/Asset Registry, moving through Data Acquisition and semantic Data Management, then advancing to Analytics and Artificial Intelligence (AI), and finally culminating in a Decision Support layer. Within this architecture, the methodological innovations include:
 - A hybrid SHM methodology that uses EGMS/InSAR data for immediate regional-scale screening and defines how in situ sensors and computer-vision inspections will be integrated during subsequent validation phases, with confidence factors used to mitigate uncertainties in sparsely sampled areas;
 - A smart metering and M&V plan fully aligned with ISO 50001 and IPMVP, featuring sub-metering strategies for key loads such as external lighting, shore power, building clusters, and photovoltaic systems;
 - A semantic model based on Brick and Haystack ontologies to ensure portable representation of assets, sensors, and multi-domain KPIs;
 - A multi-criteria prioritization methodology that jointly considers structural condition, energy and carbon benefits, and costs, supported by robustness analyses across alternative weighting scenarios.
2. The study provides a practical feasibility assessment on the Port of Formia, adopting a progressive initialization paradigm. This approach leverages the existing documentary heritage, including three-year maintenance plans, architectural surveys, design specifications, and freely available EGMS satellite data, as an initial “Data Lake” for calibration and ex-ante scenario analysis before full IoT deployment. Structural data from EGMS/InSAR play a particularly strategic role in this pre-operational phase, as they are immediately accessible without additional sensor installation and directly inform the technical feasibility and urgency of energy retrofit interventions (for instance, by verifying the absence of significant subsidence on structures intended to support photovoltaic systems or lighting towers).

By explicitly treating structural health and energy performance as coupled systems throughout the pre-operational feasibility assessment phase, the proposed framework enables coherent, evidence-based retrofit prioritization and supports the transition of brownfield ports toward low-carbon, resilient, and operationally reliable configurations.

2. Materials and Methods

This chapter describes the methodology developed for the design and pre-operational validation of the proposed energy-aware DT for the Port of Formia. The overall approach is structured according to a five-layer architecture. All procedures are intentionally situated within the pre-operational feasibility assessment phase, following the progressive initialization paradigm. Consequently, the framework relies primarily on the port’s existing documentary assets, including the Three-Year Extraordinary Maintenance Plan (2017), architectural and topographic surveys, project specifications, and freely available EGMS satellite data from the Copernicus Program, supplemented by relevant literature benchmarks. No equipment or materials were physically purchased or experimentally deployed at this stage; manufacturer details and device-specific versions will therefore be specified

during commissioning, while software and data-source information is reported through provider names, official sources, and access dates where applicable.

The results obtained at this stage provide the initial configuration and calibration logic of the proposed DT architecture and will serve as a baseline for subsequent validation once live IoT infrastructure is fully operational.

2.1. Case Study and Integrated Zoning of the Port of Formia

The Port of Formia is a multifunctional port of Category II, Class II, located on the Tyrrhenian coast of southern Latium (41°15' N, 13°36' E). The port serves passenger functions (ferries to the Pontine islands: Ponza and Ventotene), commercial (cruise ships), fishing, and tourism (nautical leisure), with a water area of approximately 165,000 m² and capacity for approximately 500 berths. The state-owned area includes operational buildings (Port Authority office, warehouses, commercial concessionaire activities), public utility infrastructure (external lighting with 12 existing lighthouses and 4 planned, vessel supply poles, water and fire-fighting systems), open spaces (parking, aprons), and photovoltaic systems in the design phase (70 kWp and 20 kWp PV canopies). The Three-Year Extraordinary Maintenance Plan (2017, Lazio Region/Evolmente S.r.l.) and the Infrastructure Improvement and Adaptation Program document in detail the existing conditions and planned interventions.

To support the DT framework, the port territory has been divided into four functional zones. This integrated zoning combines the official infrastructure classification from the regulatory Plan with the spatial distribution of energy assets and structural monitoring points (Table 3).

Table 3. Integrated zoning of the Port of Formia. For each zone, building assets, existing and planned energy systems, and EGMS points available for structural monitoring are reported.

Zone	Main Function	Main Buildings/Structures	Existing Energy Systems	Planned Retrofit Interventions	EGMS Points
A Azzurra quay and landside services	Passengers, Pontine Islands ferries, Guardia di Finanza, landside services	Harbor Master's Office, Freezing Fish warehouse (1538 m ²), Harbor Master's Office parking area, bus stop	Main switchboard (POD), 3 high-mast towers, yard and quay lighting	PV canopies for the Harbor Master's Office parking area (70 kWp, EUR 180 k), PV canopies for the bus stop (20 kWp, EUR 170 k), LED lighting upgrade	5
B Vespucci pier and apron	Commercial activities, Pontine Islands ferry landing, cruises	Vespucci apron, embarkation and disembarkation structures	Secondary switchboard, 3 high-mast towers	Functional upgrade of ramps and quay (EUR 200 k + EUR 400 k), signage (EUR 4 k)	3
C Breakwater and lee-side pier	Cruises, ship berthing, small-craft mooring	Outer pier, port structures on the breakwater	4 high-mast towers, lighthouse, 13 service pedestals for boats (not electrified)	4 new high-mast towers (EUR 500 k), electrification of 13 shore-power pedestals (EUR 25 k), pier upgrade (EUR 700 k)	4
D Azzurra basin/marina	Tourist boating, leisure craft, Piscine Romane	Azzurra marina, lightweight structures	2 high-mast towers, distributed lighting, CCTV system	LED lighting upgrade, CCTV maintenance (EUR 5 k), siltation monitoring (EUR 50 k)	2

The resulting zoning, illustrated in Figure 1, serves three fundamental purposes: (i) defining precise system boundaries for energy sub-metering in compliance with ISO 50001; (ii) facilitating the grouping and interpolative analysis of EGMS measurement points

for SHM; and (iii) establishing coherent units for multi-criteria prioritization of maintenance and energy retrofit interventions.

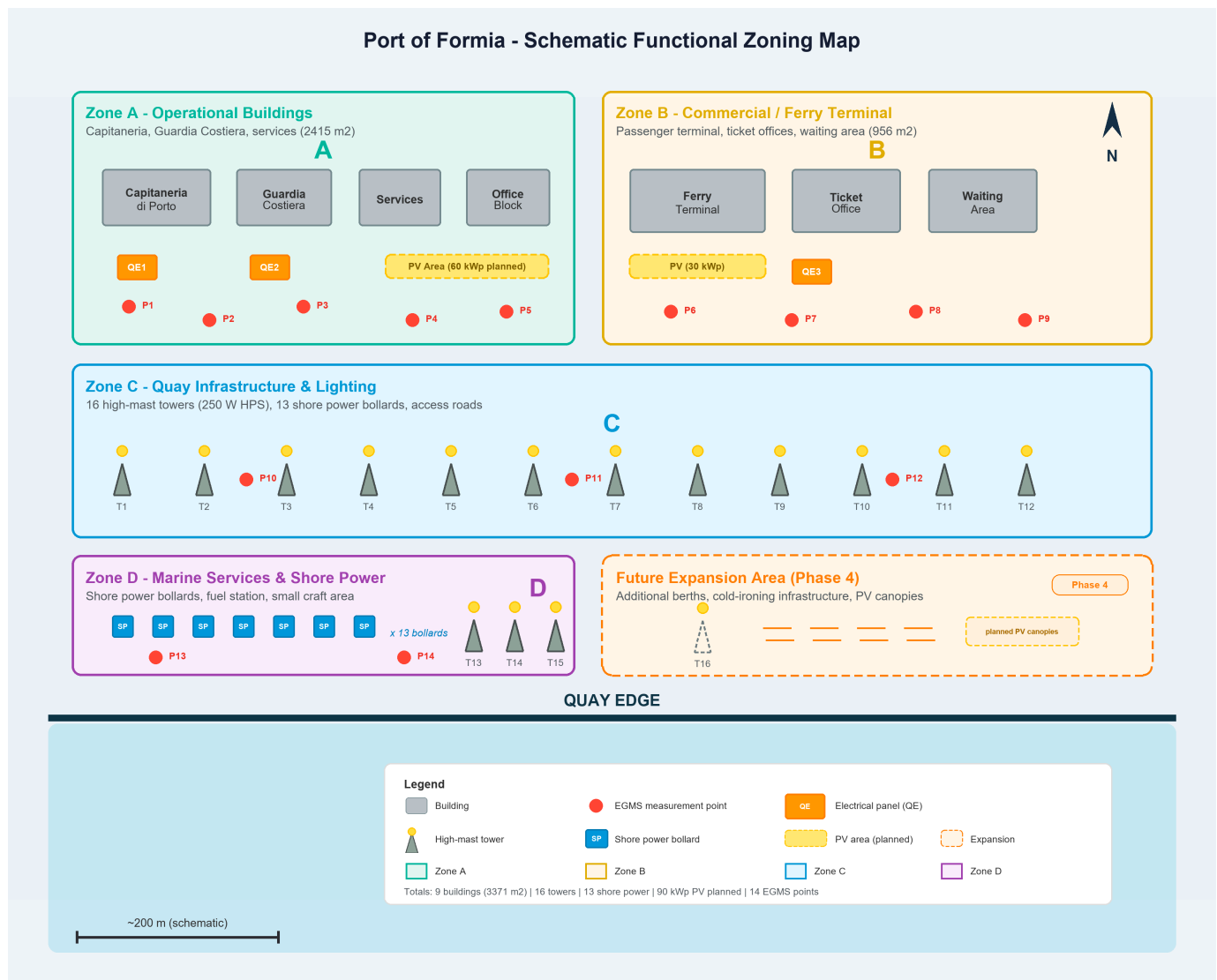


Figure 1. Schematic functional zoning map of the Port of Formia. Four zones (A–D) are defined based on operational function, with SHM monitoring points (EGMS P1–P14), high-mast lighting towers (T1–T16), electrical panels (QE1–QE3), shore power bollards, and planned PV areas overlaid.

To ensure scientific transparency, the study employs a four-category evidence taxonomy inspired by M&V protocols and the GHG Protocol [40,41]: M = measured/observed; D = document-derived; S = scenario-estimated; and V = to be validated post-implementation. This taxonomy is explicitly applied whenever KPIs are derived from pre-operational data rather than from complete pre-/post-intervention measurements.

The current implementation status is therefore separated into three levels: implemented evidence, consisting of documentary records, EGMS/InSAR screening, asset zoning, and ex-ante engineering calculations; designed components, consisting of the BIM/IoT data architecture, smart-metering map, dashboard logic, and M&V protocol; and future validation components, consisting of live smart metering, in situ SHM sensors, computer-vision surveys, trained anomaly models, and the 12-month pre/post datasets required for IPMVP-compliant verification.

2.2. Hybrid SHM-Energy DT Architecture

The proposed DT adopts the modular five-layer architecture that ensures clear separation of responsibilities, scalability, and seamless integration between SHM and energy management domains:

1. **Level 1 (BIM/Asset Registry)** provides the information schema for contribution (C) on multi-domain KPIs;
2. **Level 2 (Data Acquisition)** implements the unified sensor infrastructure for contributions (A) and (B);
3. **Level 3 (Data Management)** ensures Brick/Haystack shared semantics;
4. **Level 4 (Analytics/AI)** produces SHM scores and energy indicators;
5. **Level 5 (Decision Support)** implements the multi-criteria prioritization of contribution (D).

From a methodological perspective, the architecture is reinterpreted as a cyber-physical system for a small constructed port district, in which buildings, external lighting, supply poles, and photovoltaic systems are treated as interconnected functional blocks, consistent with district-scale distributed energy system thinking [42]. Consistent with recent DT approaches for energy management, the BIM model is not merely a geometric container, but the information layer that enables linking asset IDs, functional zones, sensors, retrofit scenarios, and real-time data flows in a single decision infrastructure.

The proposed architecture, illustrated above in Figure 2, is organized according to a layered model that separates responsibilities and enables scalability:

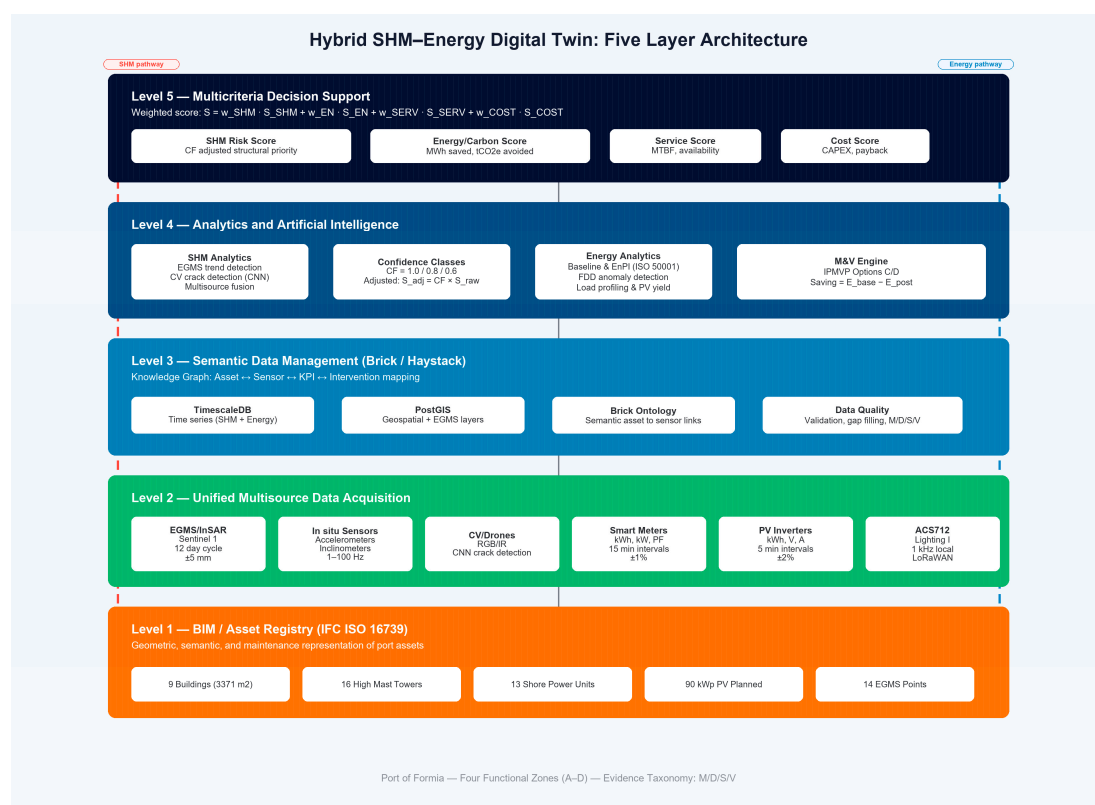


Figure 2. Five-layer architecture of the hybrid SHM–Energy DT. From the bottom: Level 1 (BIM/Asset Registry) provides the geometric and semantic asset base; Level 2 (Data Acquisition) unifies multi-source IoT and satellite inputs; Level 3 (Semantic Data Management) maps assets, sensors, and KPIs via Brick/Haystack ontology; Level 4 (Analytics/AI) computes SHM risk scores and energy performance indicators; Level 5 (Decision Support) integrates weighted multi-criteria scoring. Dashed vertical lines and color groupings indicate cross-layer information flows and domain-specific SHM/energy pathways.

2.2.1. Level 1: BIM/Asset Registry

The system provides a geometric, semantic, and maintenance representation of port assets that acts as a reference schema for the entire platform. Its purpose is to create a unified description of the port infrastructure, enabling consistent integration between physical assets, monitoring systems, and maintenance processes. The core of it is a three-dimensional BIM representation encoded in IFC format (ISO 16739 [20]).

The model includes the main elements of the port environment, such as buildings, electrical switchboards, lighthouses, lighting poles, photovoltaic systems, wharves, piers, and functional areas. Each asset is associated with a persistent unique identifier and classified according to its type (e.g., building, lighting system, pole). In addition, assets are georeferenced through geodetic coordinates and described using geometric attributes such as volume, surface area, height, and orientation. Information about materials and the current maintenance status of each asset is also included. For each asset, the system maintains a structured maintenance record containing information on critical components, estimated useful life, and, where available, the history of maintenance interventions. The record also stores criticalities identified through SHM systems or inspection activities, following established asset management principles to support maintenance planning and decision-making. From a technological perspective, the BIM model is exchanged and stored using the IFC standard, while geometric and spatial data are managed through a PostGIS spatial database that enables efficient geographic queries. Semantic relationships between assets, sensors, KPIs, and maintenance interventions are modeled through the Brick ontology, which provides a semantic layer connecting physical infrastructure with monitoring and operational data.

2.2.2. Level 2: Data Acquisition

This layer is responsible for the ingestion, temporal synchronization, quality tagging, and initial processing of heterogeneous data streams from both the SHM and energy domains. In contrast to traditional architectures that maintain separate subsystems for structural and energy data, the present framework adopts a unified data acquisition infrastructure. This approach reduces redundancy, improves temporal consistency across domains, and facilitates more effective cross-domain analytics and decision support in the upper layers. The overall architecture of the data ingestion layer, encompassing both SHM and energy flows, is illustrated in Figure 3.

As shown in Figure 3, the architecture is organized into several functional sublayers:

- **Edge/Pre-Processing Layer:** Performs initial conditioning and lightweight analytics close to the data source (sensor conditioning for in situ SHM sensors, CNN-based crack detection for computer vision, RMS computation and harmonic analysis for current sensors on lighting lines).
- **Gateway and Transport Layer:** Includes LoRaWAN gateways (with NTP synchronization and zone-based coverage), ChirpStack Network Server for packet deduplication and routing, Copernicus API for scheduled EGMS/InSAR downloads, and the Security API Layer (OAuth authentication and encryption in-transit).
- **Integration and Stream Processing Layer:** Comprises Apache NiFi for data routing and transformation, a message broker (Kafka or RabbitMQ), Apache Flink for real-time stream processing and windowed aggregation, and a dedicated Data Quality Engine that applies range checks, coherence validation, and quality flagging according to the M/D/S/V taxonomy.
- **Multi-Engine Persistence Layer:** Utilizes TimescaleDB for time-series data, PostGIS for geospatial information (including EGMS layers and asset locations), Cassandra for high-frequency raw data, and object storage for computer vision images.

and BIM models. Semantic enrichment is performed through the Brick/Haystack knowledge graph.

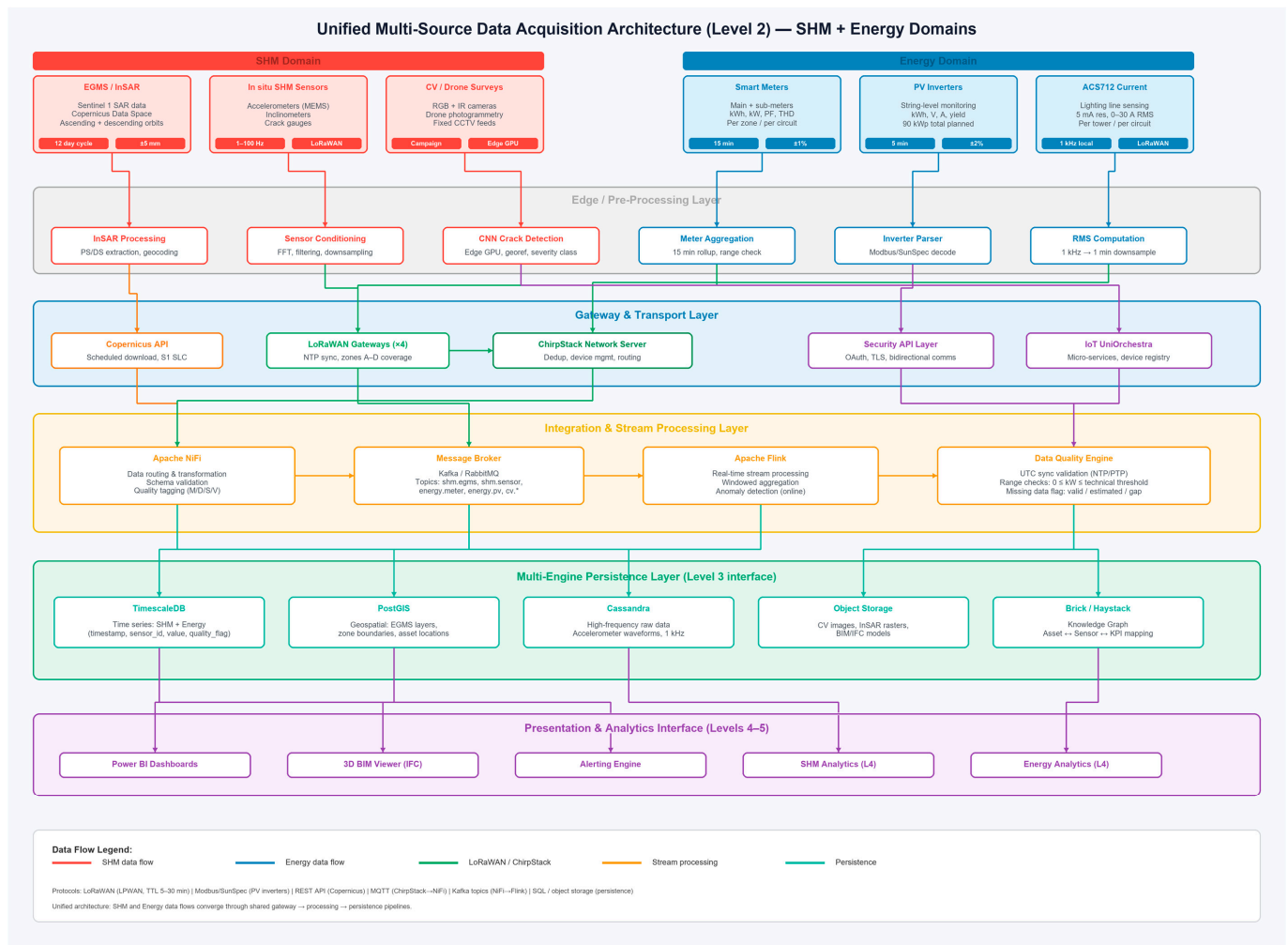


Figure 3. Unified multi-source data acquisition architecture (Level 2). SHM sources (EGMS/InSAR, in situ sensors, CV/drones) and Energy sources (smart meters, PV inverters, ACS712 current sensors) converge through edge pre-processing, LoRaWAN gateways and ChirpStack into a shared NiFi/Flink stream processing pipeline with multi-engine persistence (TimescaleDB, PostGIS, Cassandra). Purple arrows identify the shared acquisition-to-processing pathway. Here, cv.* means all message topics related to computer vision: cv is the prefix for computer vision, and * represents any following topic name.

The LoRaWAN gateway serves as a central convergence point for both SHM sensors (MEMS accelerometers, inclinometers, and crack gauges) and energy sensors (smart meters, ACS712 current sensors on lighting lines, and PV inverter data). EGMS/InSAR data and computer vision images are acquired through dedicated pipelines (periodic downloads from the Copernicus Data Space Ecosystem and georeferenced drone or fixed-camera surveys). Implementation technologies include:

- **Ingestion Layer:** LoRaWAN Gateways with configurable intervals (1 min, 5 min, 30 min), ChirpStack Network Server, and UniOrchestra IoT microservices.
- **Security API Layer:** Bidirectional secure communication with OAuth authentication and encryption in-transit.
- **Integration and Persistence Layer:** Apache NiFi, Apache Flink, multi-engine persistence (TimescaleDB, PostgreSQL/PostGIS, Cassandra).

- Presentation Layer: 3D BIM viewer (IFC), Power BI dashboards, and alerting engine.
- Detailed specifications of the main data sources, including type, frequency, accuracy, latency, and primary use, are provided in Table 4.

Table 4. Data acquisition layer. Each source has specifications for frequency, accuracy, and utility for SHM vs. energy monitoring.

Source	Data Type	Frequency	Accuracy	Latency	Primary Use
EGMS/ Copernicus [43]	Vertical/horizontal deformation (m)	12 days	±5 mm	Days	Preventive SHM, risk zoning
In situ sensors (accelerometers, inclinometers)	Acceleration (m/s ²), angle (mrad)	1–100 Hz	±0.5 mg	Seconds	Dynamic and seismic monitoring
Computer vision (drones, cameras)	Images (RGB/IR)	Weekly/monthly	Scene-dependent	Days	Crack detection, digital inspection
Smart meter (LV grid)	kWh, kW, PF, harmonics	15 min–1 h	±1%	Minutes	Energy, demand, FDD
Inverter PV	Generated kWh, V, A, frequency	5–15 min	±2%	Minutes	Renewable production, yield
BMS/climate sensors	T, RH, CO ₂ , lux	1–15 min	Variable	Minutes	Energy correlation, comfort
Maintenance logs	Event, date, component, intervention type	On-event	N/A	Variable	Decision support, trend analysis

2.2.3. Level 3: Data Management

This layer is responsible for data management and semantic integration, whose function is to store, synchronize, and enrich the acquired data in order to create a single source of truth for the entire platform. This layer ensures that heterogeneous datasets coming from monitoring systems, energy infrastructure, and external sources are consistently organized and accessible for analysis and decision-making. The system relies on multiple complementary storage components. Time-dependent measurements, such as energy consumption and SHM signals, are stored in a time-series database (e.g., TimescaleDB or InfluxDB), which enables efficient handling of large volumes of timestamped data. All measurements are synchronized using UTC timestamps, maintained through NTP or PTP protocols to guarantee temporal consistency across gateways and edge nodes. Spatial and infrastructural information is instead managed within a geospatial database based on PostGIS, which stores asset geometries, port functional zoning, asset locations, and external geospatial layers such as EGMS data.

To support semantic interoperability, the platform integrates a knowledge graph based on the Brick or Haystack ontology [22]. This semantic layer establishes explicit relationships between assets, sensors, KPIs, and maintenance interventions. For instance, a lighthouse asset (e.g., Torre Faro Molo Sud) can be linked to a current sensor installed on its electrical line, which in turn feeds a KPI representing lighting energy consumption for the corresponding port zone. When an intervention such as an LED retrofit is performed, the knowledge graph updates the relationship between the asset and its sensors and introduces new performance indicators, such as lighting efficiency expressed in energy consumption per operating hour.

To ensure the reliability of the stored information, the system implements several data quality and validation mechanisms. Temporal synchronization guarantees consistent timestamps across all sources. Missing or incomplete data are handled through quality flags (e.g., valid, estimated, or gap), while conservative imputation rules may be applied for analytical purposes but are not permitted for formal M&V processes without explicit

authorization. Additional validation procedures include range checks, ensuring that measured values remain within technically plausible thresholds (for example, verifying that circuit power consumption remains within expected limits and that the sum of sub-meter readings is consistent with the main meter within acceptable error margins). Finally, automated anomaly detection techniques—such as autoencoder or Isolation Forest models—are used to identify abnormal patterns in the data, which may indicate sensor malfunctions or unusual operational conditions.

2.2.4. Level 4: Analytics and AI

The analytics layer is structured into two main subsystems, dedicated respectively to structural monitoring and energy performance analysis:

- The SHM Analytics Subsystem focuses on the analysis of structural behavior through a staged integration of monitoring sources. In the present case study, the demonstrated empirical layer is the EGMS/InSAR screening dataset. Zone-level polynomial fitting is applied only where the density of InSAR points is sufficient to ensure reliable spatial representation. In locations where the data are sparse, the workflow does not attempt robust zonal modeling; instead, it provides screening-level evidence that can trigger targeted inspections or further monitoring activities. Multi-source fusion with GNSS measurements, accelerometers, inclinometers, crack gauges, or visual-inspection data is specified as a validation step to be implemented after field deployment. Similarly, the computer-vision pipeline is reported here as a designed inspection workflow, not as a model trained or tested on Formia images.
- The Energy Analytics Subsystem supports the analysis and optimization of energy consumption within the port infrastructure. The first analytical component concerns the definition of energy baselines and Energy Performance Indicators (EnPIs). Baselines are established using at least twelve months of preliminary data and can be expressed either in absolute terms (total kWh) or in normalized forms such as kWh/m² for buildings or kWh per operating hour for lighting systems. The baseline definition includes stratification by functional zone and seasonal patterns, integrating spatio-temporal energy profile modeling [44,45] and broader building energy information and data analytics approaches [46,47].

Another key element is the implementation of Fault Detection and Diagnostics (FDD) methods. These algorithms analyze load profiles and equipment behavior in order to identify anomalies, such as lighting systems operating during daytime hours, abnormal nighttime consumption, LED degradation, failed ballasts, or malfunctioning sensors. The subsystem also incorporates anomaly detection techniques applied to smart meter data [48]. In parallel, load profiling procedures aggregate and analyze energy consumption patterns in order to identify demand peaks, evaluate load factors, and derive typical consumption curves for specific circuits or functional zones. Finally, the subsystem computes a set of energy efficiency KPIs, including photovoltaic yield (kWh/kWp), PV load factor, self-consumption percentage, and self-sufficiency percentage, as well as lighting efficiency indicators such as lux per watt.

Machine learning approaches developed for SHM and image object detection can also support future energy and inspection modules [49,50]. Likewise, smart-grid learning methods and sensor-network transmission strategies are relevant to future operational deployment of the metering layer [51,52]. No AI model has yet been trained, tested, or validated on live Port of Formia data; AI is therefore treated as a planned analytics capability rather than an achieved empirical result.

2.2.5. Level 5: Decision Support

This layer supports the prioritization of maintenance and retrofit interventions for the built environment by integrating information on structural conditions, energy and carbon benefits, operational continuity, and economic feasibility. The objective is to assist decision-makers in identifying the most effective interventions by combining technical monitoring results with performance indicators and cost considerations.

The decision-making process is structured around four main pillars:

- The first concerns structural criticality and risk, derived from SHM analytics. The evaluation is based on indicators such as InSAR deformation trends, results from computer vision crack detection, and the reliability of historical monitoring data. These elements contribute to a risk score that typically ranges from “green,” indicating stable conditions with no significant anomalies, to “red,” indicating a critical trend that may require urgent intervention.
- The second pillar considers energy and carbon benefits associated with potential retrofit actions. These are evaluated through KPIs derived from metering data and analytical models, such as the variation in Energy Use Intensity (EUI) before and after the intervention, the estimated annual energy savings in kWh, the potential reduction in greenhouse gas emissions expressed in kg CO₂e, and the expected energy payback time. While these values can be calculated accurately only after the implementation of a retrofit through formal M&V procedures, the preliminary screening phase relies on literature benchmarks combined with conservative adjustment factors.
- The third dimension addresses service continuity and operational impacts within the port environment. In this context, the analysis considers reliability indicators such as estimated Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR), the expected downtime associated with interventions, and the potential impacts on port activities such as passenger services, fishing operations, or recreational boating. Maintenance constraints and operational scheduling requirements are also taken into account in order to minimize disruptions.
- The fourth pillar focuses on economic feasibility and implementation constraints. This includes the evaluation of capital expenditures (CAPEX), operational expenditures (OPEX), cost indicators such as cost per installed kWp or cost per intervention point, as well as regulatory requirements and technical prerequisites that may influence the feasibility of a retrofit.

Methodologically, the prioritization process can be implemented through a transparent weighted scoring approach, which allows criteria and weights to be easily updated as new information becomes available. Alternatively, more formal multi-criteria decision-making (MCDM) methods, such as AHP, TOPSIS, or ELECTRE, may be adopted when it is necessary to capture non-linear trade-offs between criteria and to explicitly incorporate decision-maker preferences [53,54]. Such multidimensional prioritization approaches are widely recognized as essential tools for enhancing the resilience of urban infrastructure systems [55] and for optimizing investment strategies in building and infrastructure retrofits [56].

2.3. The Hybrid SHM Methodology

The hybrid SHM methodology integrates three complementary observation scales to deliver reliable zone-level structural assessments while addressing the intrinsic limitations of each data source:

2.3.1. EGMS-Based Displacement Analysis and Interpolation-Based Thresholding

The EGMS provides vertical and horizontal deformation data from InSAR (Synthetic Aperture Radar Interferometry) with millimeter precision and periodic update [32–34]. For

the Formia Port, the EGMS Ortho dataset is used, which combines absolute deformation information and InSAR coherence for each measurement point (MP). Once EGMS data (vertical displacement in mm for each point) is acquired, interpolative analysis proceeds to extend knowledge of motion to directly unmonitored points, using InSAR coherence methodologies for validation [57]. A 2D polynomial regression model is adopted on geographic coordinates (East, North). The SHM parameters adopted for the different zones of the Port of Formia are summarized in Table 5.

Table 5. SHM parameters for Formia Port zones. A calibrated polynomial fit is reported only for Zone A; for zones with sparse EGMS coverage, only screening-level evidence and inspection triggers are reported.

Zone	Alarm/Inspection Threshold	Interpolation/Evidence Type	Fit Quality/Confidence	Polynomial Fit	No. of MPs
A	+/-15 mm	$z = 2.1 E - 5 \cdot E + 3.2 E - 6 \cdot N + 0.12$	$R^2 = 0.7432$	Grade 2	5
B	Inspection trigger only	Single EGMS point; no robust zonal interpolation	Screening only (CF = 0.6)	n.a.	1
C	Inspection trigger only	Single EGMS point; no robust zonal interpolation	Screening only (CF = 0.6)	n.a.	1
D	Inspection trigger only	Single EGMS point; no robust zonal interpolation	Screening only (CF = 0.6)	n.a.	1

Settlement threshold limit: The meaning of the alarm threshold is linked to the R^2 goodness-of-fit index of the polynomial fitting: $-1 \geq R^2 \geq 0.90$: Excellent fitting. Threshold limit equals $\pm 10\%$ of the predicted value. $-0.90 > R^2 \geq 0.80$: Good fitting. Threshold limit equals $\pm 20\%$ of the predicted value. $-0.80 > R^2 \geq 0.70$: Moderate fitting. Threshold limit equals $\pm 30\%$ of the predicted value. $-0.70 > R^2 \geq 0.60$: Poor fitting. Threshold limit equals $\pm 40\%$ of the predicted value.

This stratification reflects the conservative principle that the more uncertain the model (low R^2), the wider the tolerance must be before triggering an alarm.

2.3.2. Confidence Classes and Adjusted Structural Scoring

To avoid overinterpretation of satellite data, the interpolated result is not treated as an autonomous structural diagnosis. As recalled by EGMS documentation, interpretation of individual measurement points requires caution, especially in areas with low point density or with possible local deviations not represented by the cluster [58,59].

Consequently, the structural score is corrected via a confidence factor CF that depends on the quality of the observed cluster and the availability of multi-source confirmations. The confidence classes adopted in this study are presented in Table 6.

The final adjusted structural score is computed as Equation (1) ensuring that subsequent prioritization remains conservative and proportionate to data quality. This keeps the hybrid prioritization responsive to structural evidence without treating sparse satellite observations as if they were equivalent to dense in situ monitoring [58,59].

$$S_{\text{SHM, adj}} = CF \times S_{\text{SHM, raw}} \quad (1)$$

From EGMS time series (every 12 days), six-monthly displacement velocities are calculated via linear regression for each zone (Equation (2)):

$$v_z = \Delta z / \Delta t \text{ [mm/year]} \quad (2)$$

with $\Delta t = 0.5$ years for six-monthly comparison.

Table 6. SHM confidence classes adopted to avoid overclaiming from sparse EGMS evidence.

Decision-Support Use	Interpretation	Typical EGMS Condition	Confidence Class
Full structural score used in hybrid ranking	Trend can support prioritization directly	≥ 5 MPs in zone, coherent cluster, no isolated outlier, optional local confirmation	High (CF = 1.0)
Structural score discounted before ranking and field check recommended	Screening trend is informative but not conclusive	3–4 MPs or moderate coherence, partially stable cluster	Medium (CF = 0.8)
No stand-alone diagnosis; in situ sensing or inspection required before decisions	Only a trigger for targeted inspection	1–2 MPs, low coherence, or isolated point behavior	Low (CF = 0.6)

Delta z is the mean vertical displacement calculated from the interpolating polynomial between two six-month periods and Delta t is the temporal interval considered. In the present work the threshold $v_z > 5$ mm/year is used as a screening alert threshold to activate additional local verification in the coastal environment, not as a universal limit of damage or structural failure.

The results of the interpolative analysis for each zone, including polynomial fitting and confidence intervals, will be presented in Section 3 (Figure 4).

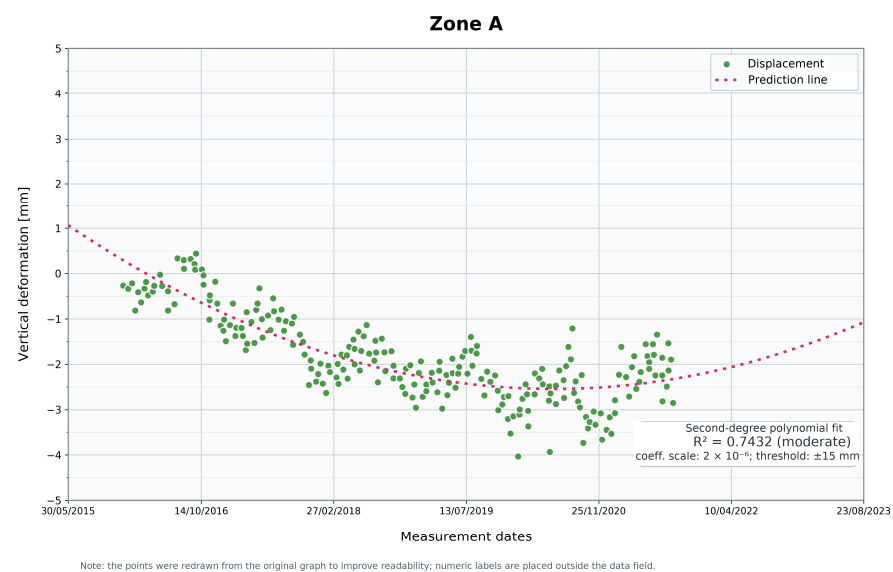


Figure 4. Dispersion of displacement data for Zone A and polynomial fitting second-degree. $R^2 = 0.7432$ indicates moderate fitting; confidence interval for prediction is broad.

2.3.3. Integration of In Situ Sensors and Computer Vision

When the EGMS analysis indicates a slow deformation trend or a localized anomaly, the monitoring workflow activates a targeted verification process based on additional sensing and inspection techniques.

The first step consists of the installation of in situ sensors to provide higher temporal resolution and confirm the observed behavior. Typical instruments include MEMS accelerometers (± 2 g range, sampling frequency up to 100 Hz), inclinometers with approximately 0.1 mrad resolution, and contact crack gauges installed on known fractures. These sensors enable continuous monitoring and allow the detection of rapid dynamics that cannot be captured by satellite observations alone, such as impacts, microearthquakes, or sudden structural responses. Furthermore, the integration of InSAR measurements with

local GNSS observations can significantly strengthen the validation of detected deformation trends and improve the reliability of the monitoring results [60].

In parallel, the workflow may include digital visual inspection based on computer vision techniques once a photographic survey campaign is available. Georeferenced images acquired by drones or fixed cameras would be processed through deep-learning models, typically convolutional neural networks such as ResNet, YOLO, or improved Faster R-CNN object-detection approaches [50,61], to detect cracks or other visible damage patterns. In the present submission this component remains a planned validation module; its outputs are not used as empirical evidence for the Formia prioritization.

The integrated computer vision pipeline follows a structured sequence of processing steps. First, georeferenced images are acquired and subjected to pre-processing operations such as histogram equalization and filtering to enhance relevant features. The processed images are then analyzed using a convolutional neural network for crack detection. Subsequently, post-processing procedures, such as clustering of detected pixels and spline fitting of crack patterns, are applied to refine the results.

Finally, the detected features are mapped onto the EGMS spatial layer, enabling direct comparison with satellite-derived deformation data and triggering alerting procedures when spatial overlap between visual damage and critical deformation points is identified.

2.4. Energy Monitoring, Smart Metering, and M&V Methodology

This section details the methodology for energy monitoring, smart metering, and M&V. The energy subsystem is formulated as a metering and analytics platform compliant with ISO 50001 [24], ISO 50015 [25], and IPMVP [26], connected to the unified data acquisition architecture.

2.4.1. Smart Metering and Sub-Metering Plan

The built environment has complex low-voltage electrical infrastructure with distributed distribution boards and diversified loads. A smart metering strategy compliant with ISO 50001 requires hierarchical measurement on multiple levels, with granularity chosen to respond to specific energy objectives [38–49,53–65]. The proposed smart metering and sub-metering plan is presented in Table 7.

Table 7. Smart metering and sub-metering plan for Formia Port. Each point has granularity specifications and usage aligned to ISO 50001.

Primary Use	Measurement Type	Temporal Granularity	Circuit/Asset	Measurement Point
IPMVP Option C, billing	kWh, kW, PF	15 min	Whole port facility	Main delivery point (POD)
Baseline lighting, FDD	kWh, A, V, harmonics	1–5 min	High-mast towers + yard lighting	Lighting switchboard
Boat-service billing, anomaly detection	kWh per bollard, kW	1 min	13 boat service pedestals	Bollard switchboard
EUI, benchmarking	kWh, kW	15 min	Cluster of 9 buildings or individual buildings	Building switchboard
Yield, self-consumption, self-sufficiency	kWh prodotto, DC V/A, AC V/A	5 min	PV 70 kWp	Parking PV inverter
Yield, self-consumption	kWh prodotto, DC V/A, AC V/A	5 min	PV 20 kWp	Bus-stop PV inverter
Energy correlation, comfort	°C, %, ppm	15 min	Building interiors (T, RH, CO ₂)	BMS/environmental sensors

2.4.2. Outdoor-Lighting Monitoring Through Current Sensing and Predictive Maintenance

Since in comparable port contexts external lighting accounts for approximately two-thirds of total electrical consumption [28–36], the proposed framework includes a dedicated subsystem for continuous monitoring and predictive maintenance of lighting infrastructure. This subsystem allows detailed tracking of consumption patterns and early detection of faults affecting lighting circuits and related equipment.

At the sensing level, the system employs current sensors (e.g., ACS712 or equivalent) installed on the electrical lines supplying beacon towers and main lighting circuits. These sensors operate with a measurement range of 0–30 A RMS and a resolution of approximately 5 mA. Local acquisition occurs at a sampling rate of about 1 kHz in order to capture detailed electrical behavior; the data are then downsampled to one-minute intervals for transmission via LoRaWAN, balancing measurement fidelity with low-power communication constraints.

Sensor data are transmitted to a LoRaWAN gateway, which acts as the convergence point for the monitoring network. The gateway manages packet reception with a time-to-live typically ranging between 5 and 30 min, consistent with LPWAN communication characteristics, and ensures temporal synchronization through the Network Time Protocol (NTP). The packets are then forwarded to the ChirpStack Network Server, which performs packet deduplication and routes the data toward the central data platform.

Once received by the platform, the measurements are processed through a data processing pipeline based on Apache NiFi and Apache Flink. Within this pipeline, the one-minute data streams are aggregated to fifteen-minute intervals for dashboard visualization and analytical purposes. Additional feature extraction procedures compute relevant electrical parameters such as RMS current, power factor, and Total Harmonic Distortion (THD). These features would support anomaly detection algorithms after commissioning and training on operational data; in the present study, however, autoencoder-based or similar models are proposed future modules rather than validated Formia results. Typical anomalies may include constant current during daylight hours, suggesting photocell malfunction, or sudden increases in THD that may indicate degraded ballasts or other electrical issues.

All processed measurements are stored in a TimescaleDB time-series database, following a structured schema that includes fields such as timestamp, sensor identifier, RMS current, power factor, THD, and anomaly status. The resulting dataset feeds a Power BI dashboard, which provides real-time visualization of lighting energy consumption by zone, as well as weekly and monthly trends. The dashboard also supports automated alerting mechanisms when critical anomalies are detected.

The focus on external lighting is motivated by considerations of energy representativeness in Mediterranean port environments. Beacon towers and yard lighting circuits typically constitute a significant and highly visible share of electrical demand. Moreover, these systems are relatively easy to sub-meter and therefore well suited for scenario-based comparisons, including the evaluation of current operational conditions, LED retrofit scenarios, adaptive lighting control strategies, and predictive maintenance approaches. For these reasons, the monitoring of current and power quality in lighting circuits is considered the first operational module of the energy-aware DT.

2.4.3. Baselines and Energy Performance Indicators (EnPIs)

Once twelve months of preliminary measurements are available, or equivalent historical datasets where accessible, the system defines a set of energy baselines for the main consumption categories within the port infrastructure. These baselines represent the reference conditions against which future performance improvements and retrofit impacts can be evaluated.

For external lighting, the baseline is expressed in terms of annual energy consumption (kWh/year) or normalized consumption per equivalent operating hour (kWh/equivalent hour). It corresponds to the average consumption under normal operating conditions, excluding seasonal peaks or exceptional interventions such as temporary installations or maintenance events. Predictable variability related to seasonal changes in daylight duration is incorporated through regression against the day-of-year parameter, following consolidated energy performance assessment methodologies [47].

For floating electrical outlets, the baseline is defined using annual energy consumption (kWh/year) or consumption per charging event (kWh/charging event). In this case, historical consumption data are normalized according to operational parameters such as the average number of moored vessels and the average duration of mooring periods. This normalization also considers the thermal inertia of onboard and shore-side electrical systems, which may influence energy demand patterns [66].

For buildings within the port area, the baseline is expressed either as total annual consumption (kWh/year) or as a normalized indicator such as energy use intensity (kWh/m²). Where buildings are equipped with heating or cooling systems, the baseline is further normalized using heating and cooling degree-days, allowing seasonal climatic variability to be incorporated into the energy performance assessment.

For photovoltaic installations, the expected performance baseline is expressed as annual energy yield per installed capacity (kWh/kWp/year). Reference values are derived from the PVGIS database or from manufacturer technical specifications. For the Formia case study, the preliminary reference range is estimated between 1288 and 1521 kWh/kWp/year, depending on factors such as panel orientation and system losses [67]. These values are consistent with photovoltaic performance studies conducted in Mediterranean climates as well as with standard solar engineering references [68,69].

Following the implementation of a retrofit intervention—such as an LED lighting upgrade—the baseline is recalculated for the post-intervention period. Energy savings are then quantified by comparing the normalized baseline consumption with the normalized post-retrofit consumption according to the following relationship in Equation (3):

$$\text{Saving} = E_{\text{baseline,normalized}} - E_{\text{post,normalized}} \quad (3)$$

2.4.4. M&V Plan Aligned with IPMVP

In compliance with the IPMVP, two possible M&V approaches are considered for the Port of Formia, depending on the complexity of the retrofit interventions.

The primary approach proposed is IPMVP Option C, based on whole-facility metering combined with statistical adjustments for contextual variables. In this configuration, the measurement boundary corresponds to the entire port facility, represented by the main electricity supply point (POD). The baseline is defined as the average electricity consumption recorded during the twelve-month period preceding the retrofit, with seasonal adjustments applied through indicators such as heating or cooling degree-days when relevant. After the intervention, post-retrofit measurements are collected through continuous monitoring for at least twelve months, ensuring that the evaluation period captures the full range of seasonal operational conditions.

To improve comparability between the baseline and the reporting period, the analysis includes normalization procedures that adjust for uncontrolled variables such as weather conditions, vessel occupancy levels, or the number of passenger-related events within the port area. When sufficient historical data are available, these adjustments can be performed through multiple regression models. Under typical monitoring conditions, the expected accuracy of this approach is approximately $\pm 10\text{--}15\%$, depending on the quality of the available measurements and the completeness of contextual variables.

For more complex retrofit scenarios, such as simultaneous interventions involving both HVAC systems and lighting infrastructure, an alternative approach is IPMVP Option D, based on calibrated simulation models. In this case, a pre-retrofit physical model of the facility is developed using simulation tools such as EnergyPlus [70] or TRNSYS. The model incorporates detailed information derived from BIM geometry, including building orientation, thermal transmittance values, and occupancy or operational profiles. The model is then calibrated using measured energy consumption data from the twelve-month pre-retrofit period, adjusting parameters until the simulated results match the measured data within a tolerance of approximately $\pm 5\%$.

Once calibrated, the model is updated to represent the post-retrofit configuration, for example by modifying parameters related to LED lighting efficiency or HVAC operating setpoints. The system performance is then simulated over a virtual twelve-month period, and energy savings are calculated as the difference between the simulated pre-retrofit and post-retrofit scenarios. When the model calibration is robust, this approach can achieve an accuracy of approximately $\pm 5\text{--}8\%$, which is generally higher than Option C; however, it requires significantly greater modeling effort and specialized expertise.

Considering that the planned interventions for the Port of Formia primarily concern lighting upgrades and photovoltaic integration, IPMVP Option C represents a realistic and sufficiently accurate solution for the M&V of energy savings.

2.4.5. Emission Factors for Operational Carbon Tracking

For carbon impact calculation, a location-based approach consistent with GHG Protocol Scope 2 Guidance [41] is adopted.

The primary factor used for results is the Italian national factor for electricity consumption in 2023, equal to $0.2347 \text{ kgCO}_2/\text{kWh}$ according to ISPRA [71]. The preliminary 2024 value of $0.1989 \text{ kgCO}_2/\text{kWh}$ is used only as a sensitivity check, not as the primary reporting factor, as shown in Table 8.

Calculation of CO_2 avoided from PV (main reporting, ISPRA 2023) (4):

$$\text{CO}_2\text{-avoided,PV} = E_{\text{displaced,PV}} \times \text{EF}_{\text{grid,2023}}, \text{ where } E_{\text{displaced,PV}} = E_{\text{self-consumed,PV}} + E_{\text{export,credited}}. \text{ Gross-displacement upper bound: } (116\text{--}137) \text{ MWh/year} \times 0.2347 \text{ kgCO}_2/\text{kWh} = 27.2\text{--}32.1 \text{ tCO}_2\text{e/year} \quad (4)$$

Calculation of CO_2 avoided from lighting retrofit (main reporting, ISPRA 2023) (5):

$$\text{CO}_2\text{-avoided,lighting} = E_{\text{saved}} \times \text{EF}_{\text{grid,2023}} = (31.5\text{--}36.8) \text{ MWh/year} \times 0.2347 \text{ kgCO}_2/\text{kWh} = 7.4\text{--}8.6 \text{ tCO}_2\text{e/year} \quad (5)$$

Table 8. Operational CO_2 emission factors and reporting boundaries adopted in this study. Main reporting uses the ISPRA 2023 electricity consumption factor; 2024 is sensitivity only.

Source	Unit	Notes	Emission Factor	Energy Carrier/ Reporting Use
ISPRA RAPPORTO 413/2025 (2023 DATA) [71]	kgCO_2/kWh	Location-based factor for electricity consumption; primary factor used in results.	0.2347	Italian national electricity—main reporting 2023
		Sensitivity check only; not the main reporting factor.	0.1989	Italian national electricity— sensitivity 2024 preliminary

Table 8. Cont.

Source	Unit	Notes	Emission Factor	Energy Carrier/ Reporting Use
GHG Protocol [41]	kgCO ₂ /kWh	Operational avoided emissions are computed against the selected grid factor, not with a separate PV factor.	Use displaced grid factor	PV avoided emissions in this study
		Avoided operational emissions follow the same location-based electricity factor.	Use displaced grid factor	Lighting efficiency interventions

3. Pre-Operational Results and Scenario Estimates

3.1. SHM Results and Displacement Analysis

This section presents the pre-operational outputs available for the case study. Only the EGMS-based displacement analysis is empirical at this stage; the energy and carbon quantities are scenario estimates derived from documentary data, technical assumptions, and literature/PVGIS benchmarks.

The moderate R^2 value (0.7432) for Zone A shown in Figure 4 confirms that satellite-derived displacement data alone provide indicative rather than definitive structural assessments, which is consistent with the confidence-class framework. For Zone A, the second-degree polynomial was fitted on $n = 5$ measurement points, yielding $df = n - 3 = 2$ degrees of freedom. While the overall model p -value (p approx. 0.12) does not reach the conventional $\alpha = 0.05$ threshold, this is expected given the very small sample size; the 95% confidence intervals for the polynomial coefficients accordingly span a wide range, reflecting the exploratory nature of the screening. Zones B, C, and D, each represented by a single usable MP, do not support a statistically meaningful zonal fit and are therefore treated only as screening-level evidence (Table 5). This constraint is explicitly acknowledged: with $n \leq 5$ points per zone, the polynomial fit serves as a spatial screening tool rather than a statistically robust predictive model, and the parabolic functional form was chosen as the simplest polynomial capable of capturing non-linear subsidence gradients without overfitting.

Zones B, C, and D contribute only preliminary screening evidence because each zone is represented by a single usable EGMS point. Their observed displacements remain useful as early warning signals, but the sparse spatial sampling prevents reliable estimation of zonal gradients, fit quality, or threshold-based area-wide behavior. Accordingly, these zones are assigned low-confidence screening status and require in situ inspection or sensor integration before structural information can support retrofit prioritization. Overall, the multi-zone analysis confirms that the EGMS approach is most informative where measurement point density is adequate and should otherwise be interpreted only as a preliminary alerting layer. Zone-by-zone outputs feed directly into the hybrid scoring model of Section 3.4, where the SHM confidence class modulates the weight of the structural component in intervention prioritization.

From the perspective of practical implications for the DT, SHM results inform three conditional decisions: (i) in Zone A, relative stability ($CF = 1.0$) does not trigger additional EGMS-based restrictions for PV planning, while standard project-level structural verification remains required; (ii) in Zone C, sparse EGMS coverage requires in situ monitoring before electrification of ferry berths; (iii) in Zones B and D, insufficient EGMS density imposes a dedicated inspection and sensor campaign as a prerequisite for any

energy retrofit intervention. This conditional logic, namely structural screening as a gate for energy prioritization, represents the main operational contribution of SHM-energy integration in the proposed framework.

3.2. Energy Baseline Assessment and Readiness Gaps

In the absence of historical metering, this section adopts the readiness assessment paradigm: for each energy domain, informative maturity is evaluated according to the M/D/S/V taxonomy (Section 2.1) and the path toward a complete measured baseline is identified. The following list summarizes the readiness status for the four main loads of the port built environment:

1. Outdoor lighting [D/S]: Installed power known from the inventory (D); annual consumption estimable from dusk-to-dawn equivalent hours $\times$ nominal power (S, range 31.5–36.8 MWh/year); measured baseline (M) requires 12 months of post-commissioning smart metering. Readiness: high, first domain that can be activated.
2. Floating power pedestals [D/V]: Number and nominal power of pedestals are known from design documents (D); seasonal load profiles are unavailable (V, requiring 12 months of metering with berth occupancy logging). Readiness: medium, activatable in parallel with lighting.
3. Climatized buildings/refrigeration units [D/S/V]: Surfaces and transmittance values known from architectural survey (D); thermal demand estimable with quasi-steady-state method UNI/TS 11300 (S); actual consumption and EUI (kWh/m²/year) to be validated post-metering (V). Readiness: low—requires BMS installation and dedicated sub-metering.
4. Auxiliary services (pumps, elevators, signage) [D/V]: Aggregate nominal powers known from electrical boards (D); operating profiles and simultaneity factors to be validated (V). Readiness: low—residual load, last priority for sub-metering.

The readiness assessment highlights heterogeneous informative maturity: the lighting domain already has documentary data (D) and scenario-based estimates (S) sufficient for a quantitative pre-operational feasibility assessment, whereas buildings and auxiliary services require completion of the metering setup phase before measured baselines can be established (M). The validation roadmap provides for progressive transition from class S to class M for all domains, with priority given to the lighting load (activatable within 3 months of commissioning) and shore-power loads (activatable within 6 months).

3.3. Ex Ante Energy and Carbon Estimates

3.3.1. KPIs Directly Computable from the Available Case-Study Documents

Based on the available technical materials (datasheets, intervention plan), only verifiable KPIs are reported in Table 9.

Table 9. KPIs quantified from available documents. Cost data and non-energy metrics are excluded.

KPI	Uncertainty	Source	Value
Number of surveyed buildings	None	Survey sheets	9
Total building area	+ / −5% (manual survey)	Sum of survey sheets	3371 m ²
Planned PV capacity	Manufacturer specifications	Intervention plan	90 kWp (70 + 20)
Number of existing high-mast towers	None	Intervention plan	12
Number of new high-mast towers	None	Intervention plan	4
Number of shore-power pedestals	None	Intervention plan	13

3.3.2. KPIs Requiring Post-Implementation Smart Metering

The following KPIs require 12–24 months of post-implementation metering and intervention data. To maintain transparency, the present study distinguishes between KPIs measurable only after metering commissioning and ex-ante quantitative estimates already defensible as a pre-operational technical feasibility assessment. The latter are not presented as verified savings, but as bounded engineering estimates, derived from actual intervention sizes, documented nominal powers, peer-reviewed benchmarks on energy DTs and port case studies, and official tools JRC/PVGIS [27,28,36,67]. For photovoltaics, the planned total capacity equals 90 kWp. Using as the upper reference the annual yield for a south-oriented fixed system estimated with PVGIS for the Formia site (approximately 1521 kWh/kWp/year) and as the conservative lower reference an East–West configuration/real-loss of approximately 1288 kWh/kWp/year, the PV portfolio of the case study corresponds to expected gross production of approximately 116–137 MWh/year. The estimate assumes fixed-tilt PV canopies, a Mediterranean irradiance profile, and system-loss/orientation uncertainty captured by the lower and upper bounds. For lighting, replacement of 12 existing search light towers averaging 1000 W with LED fixtures of 300–400 W results in installed power reduction of 7.2–8.4 kW across the retrofitted fleet. Assuming average dusk-to-dawn operation of approximately 4380 h/year, this equates to a gross technical saving of approximately 31.5–36.8 MWh/year on the replaced towers alone. Since the project also includes 4 new LED towers to extend service coverage, the final savings at port scale must be measured post-intervention; however, the lighting retrofit bundle is already quantitatively justified at the asset-by-asset level. For shore power and building clusters, conversely, the study adopts a cautious approach: no ex-ante aggregate savings percentages are assigned where vessel occupancy profiles, load simultaneity, and seasonal usage patterns are not yet metered. In exchange, the measurement boundary is already defined to enable future calculation of cluster EUI, load factor, PV self-consumption, service-specific EnPIs, and carbon indicators comparable on an annual basis [72]. The seven KPIs listed below will be calculable only after completion of phases 1–3 of the validation roadmap (Section 3.7); each is currently classified as V (to-be-validated) and its transition to M (measured) will require a minimum period of 12 months of post-metering data:

1. Pre-intervention consumption (lighting baseline, bollards, buildings);
2. Post-intervention consumption (post-LED retrofit and PV);
3. Building EUI (kWh/m²/year);
4. PV yield (kWh/kWp/year);
5. CO₂ reduction (tCO₂e/year);
6. PV energy payback (years);
7. Pre/post lighting efficiency (kWh/lux).

3.3.3. Uncertainty and Sensitivity Analysis of Ex Ante Estimates

Following IEA PVPS guidance, the PV yield is reported as a bounded scenario envelope rather than as a single deterministic forecast, because orientation, system losses, long-term irradiance variability and availability materially affect ex ante estimates [73].

The same logic is applied to the lighting bundle, for which the technical saving on replaced towers is separated from the net port-scale balance after the addition of four new LED towers. The quantitative breakdown of these ranges is detailed in Table 10.

Using the central values only for discussion, the manuscript refers to about 126.4 MWh/year for the PV bundle and 34.1 MWh/year for the technical lighting saving on the replaced towers. These values are not presented as post-intervention performance, but as bounded planning references that will be accepted, corrected, or rejected once the metering protocol has produced a complete baseline and post-retrofit dataset.

Table 10. Uncertainty-aware scenario envelope for the main ex ante energy and carbon results. Evidence classes: D = document-derived; S = scenario-estimated; V = to be validated post-implementation.

Bundle/KPI	High Case	Low Case	Central Estimate	Evidence Class	Main Uncertainty Drivers
PV annual generation	136.9	116	126.4 MWh/year	D + S → V	Orientation, losses, solar resource, inverter availability
PV gross-displacement avoided emissions (upper-bound, 2023 factor)	32.1	27.2	29.7 tCO ₂ e/year	S → V	Emission-factor year and actual yield
Lighting technical saving on replaced towers	36.8	31.5	34.1 MWh/year	D + S → V	Final LED wattage, operating hours, control strategy
Lighting avoided emissions (2023 factor)	8.6	7.4	8.0 tCO ₂ e/year	S → V	Emission factor and actual night-time profile
Shore power/building-cluster EnPIs	n.a.	n.a.	Boundary defined	D → V	Occupancy, simultaneity, seasonal service use

3.3.4. CO₂ Avoided Estimates

Applying the emission factors defined in Section 2.4.5 (2023 Italian electricity consumption factor published in ISPRA Rapporto 413/2025: 0.2347 kgCO₂/kWh), avoided emissions are calculated on the basis of grid electricity actually displaced, not automatically on total PV generation. Until measured self-consumption and export accounting are available, the PV carbon range is therefore reported only as a gross-displacement upper-bound scenario and not as a verified Scope 2 reduction.

These values represent bounded planning references, not post-intervention verified performance. They will be accepted, corrected, or rejected once the metering protocol has produced complete baseline and post-retrofit datasets (Section 3.7).

3.4. Hybrid Prioritization of Interventions

The outcome of prioritization does not depend solely on theoretical savings, but on the intersection of structural risk, energy relevance, service value, and emissions reduction potential. In this perspective, search light towers, power distribution panels, and PV supports assume a central role: they are assets in which an energy retrofit decision is credible only if accompanied by sufficient SHM evidence to reduce implementation risk and performance degradation risk. Maintenance and retrofit prioritization is based on a multi-criteria decision function that integrates the four pillars: structural risk, energy/carbon benefits, service, costs. (6) A simple weighted scoring scheme is (6):

$$\text{Score}_{\text{intervention}} = w_{\text{SHM}} \times S_{\text{SHM}} + w_{\text{EN}} \times S_{\text{EN}} + w_{\text{SERV}} \times S_{\text{SERV}} + w_{\text{COST}} \times S_{\text{COST}}, \text{ with sum of weights} = 1. \quad (6)$$

where S_{SHM} = structural risk score (0–10: 0 = stable/green, 10 = critical or confirmed anomaly); S_{EN} = energy/carbon benefits score (0–10, normalized against the highest ex-ante saving or carbon-reduction potential in the intervention set); S_{SERV} = operational impact score (0–10, based on service criticality, continuity, and downtime reduction); S_{COST} = cost-effectiveness score (0–10, inverse of specific CAPEX per functional benefit); w_i = criterion weights (sum = 1; in the case study 0.30, 0.30, 0.20, 0.20). Interventions are classified by decreasing score (high priority = high score). Applying the case study weights to the three most immediate bundles yields a preliminary quantitative screening:

lighting retrofit = 7.9/10 (S_SHM = 6, S_EN = 9, S_SERV = 9, S_COST = 8); parking PV + bus stop = 6.6/10 (5, 8, 7, 6); shore-power metered electrification = 6.4/10 (4, 7, 8, 7).

The scores are expert-derived screening values traceable to the available documentary and scenario evidence: structural scores are reduced when EGMS coverage is sparse or local confirmation is absent; energy scores reflect the bounded MWh/year and carbon ranges; service scores reflect the relevance of lighting, PV support, and shore-power assets to port continuity; and cost scores use inverse relative implementation cost. They should not be interpreted as final stakeholder preferences. In the operational phase, the same matrix can be converted into AHP, TOPSIS, or ELECTRE with stakeholder pairwise comparisons and score-uncertainty perturbation.

The result is consistent with the proposed hybrid logic: lighting remains the first target because it combines high energy and service relevance, while the PV score is moderated by the need to fully verify support and roof conditions. For greater formalism, the same scheme can be translated into MCDM methods such as TOPSIS or AHP [53].

Robustness Check of the Hybrid Prioritization

To reduce the ranking's dependence on a single expert-based weight set, a robustness check was performed in line with the MCDM literature already cited [53,54] (Table 11).

Table 11. Robustness check of the hybrid ranking under alternative weighting scenarios.

Rank Order	Shore Power	PV	Lighting	Weights (SHM/EN/SERV/COST)	Scenario
Lighting > PV > Shore	6.4	6.6	7.9	0.30/0.30/0.20/0.20	Base case
Lighting > PV > Shore	6	6.2	7.6	0.40/0.20/0.20/0.20	SHM-focused
Lighting > PV > Shore	6.6	6.8	8.2	0.20/0.40/0.20/0.20	Energy-focused
Lighting > Shore > PV	6.8	6.6	8.2	0.20/0.20/0.40/0.20	Service-focused
Lighting > Shore > PV	6.6	6.4	8	0.20/0.20/0.20/0.40	Cost-focused

The test does not replace a complete AHP with an external panel and does not perturb the uncertain criterion scores themselves; it only checks whether the ranking changes under alternative weight preferences. A future operational analysis will therefore combine weight sensitivity with score sensitivity once measured energy data and in situ SHM confirmations are available.

The first rank remains stable in all tested scenarios, which is the main practical result of the robustness check. The second and third positions may swap when service continuity or cost-efficiency is emphasized, indicating that PV and metered shore power should be considered near-term companion bundles rather than mutually exclusive alternatives. It should be noted, however, that the current sensitivity analysis varies only the criterion weights while holding the expert-derived scores fixed; since the lighting bundle scores highest on every individual criterion, its first-place ranking is guaranteed regardless of the weight distribution. Score-level perturbation, or application of AHP, TOPSIS, or ELECTRE with pairwise stakeholder comparisons, is therefore recommended as a next step in the operational phase.

3.5. Multi-Domain KPI Framework for Buildings, Services, and Infrastructure

Reformulation of KPIs in the hybrid SHM-energy perspective also enables shifting the focus toward shared building services. Beyond structural indicators, the framework emphasizes KPIs oriented to cluster building EUI, lighting energy per functional zone, PV performance, self-consumption, operational carbon intensity, and service continuity for

lighting and shore power, so as to integrate energy performance and physical reliability in the same analytical space.

The framework proposes a structured set of indicators covering the five governance pillars of the Digital Twin (DT) for port buildings. As shown in Table 12, each KPI is defined by its unit of measurement, calculation formula, update frequency, and specific target threshold, providing a comprehensive metric system for the Port of Formia across SHM, energy, carbon, operational, and economic domains.

Table 12. Multi-domain KPI for the Port of Formia. Covers SHM, energy, carbon, operational, economic.

KPI	Target	Frequency	Formula	Unit	Domain
EGMS_Displacement_Rate	≤ 2 mm/year for PV/retrofit suitability	12 days	Average EGMS-point velocity by zone	mm/year	SHM
SHM_Confidence_Class	CF ≥ 0.8 for retrofit decisions	By zone	$f(n_{\text{EGMS}}, R^2, \text{integrated sources})$	CF (0–1)	SHM
SHM_Retrofit_Gate	TRUE to proceed with intervention	Pre-retrofit	CF $\geq$ threshold AND displacement $\leq$ threshold	Boolean	SHM
EUI_Buildings	$\leq$ regional benchmark (120 kWh/m ² /year for mixed ports)	Annual	Annual building energy/3371 m ²	kWh/m ² /year	Energy
PV_Yield	≥ 1200 kWh/kWp/year (PVGIS data)	Annual	Annual PV production/90 kWp	kWh/kWp/year	Energy/Renewables
PV_SelfConsumption	$\geq 60\%$ (depends on load profiles)	Annual	Energy consumed on site/Energy produced	%	Energy/Renewables
CO ₂ _Baseline	Pre-retrofit baseline	Annual	Consumption $\times$ emission factor by energy carrier	tCO ₂ e/year	Carbon
CO ₂ _PostIntervention	−20% vs. baseline (minimum target)	Annual	Post-intervention consumption $\times$ emission factor	tCO ₂ e/year	Carbon
MTBF_Asset	≥ 8760 h (1 year without downtime)	Semiannual	Hours between significant failures	hours/event	Operational
Port_Availability	$\geq 99\%$	Monthly	Operating hours/Total hours	%	Operational

3.6. DT Implementation Feasibility

The data platform and BIM-IoT integration described in Section 2.2 were instantiated for the Port of Formia case study to demonstrate implementation feasibility. The platform architecture, detailed in Figure 6, comprises five functional layers, from IoT ingestion (Lo-RaWAN gateways, ChirpStack) through data processing (Apache NiFi, Flink, TimescaleDB) to a presentation layer with 3D BIM visualization and Power BI dashboards.

The sensor-to-decision workflow ensures that raw measurements from ACS712 current sensors, EGMS satellite data, and environmental probes are normalized, validated, and routed to domain-specific analytics within the unified pipeline.

The practical application of this architecture is reflected in the energy projections for the site. Figure 5 displays a scenario-based energy time-series projection for Zone A, highlighting the transition from a document-derived/scenario baseline proxy (D/S) to to-be-validated (V) projections over a 24-month roadmap, illustrating the expected impact of the LED retrofit and PV ramp-up.

The BIM/asset registry represents port assets in IFC-compatible logic following a hierarchical schema: buildings (9 structures, 3371 m² total), lighting infrastructure (12 existing + 4 planned high-mast towers), shore power bollards (13 units), and PV systems (90 kWp planned).

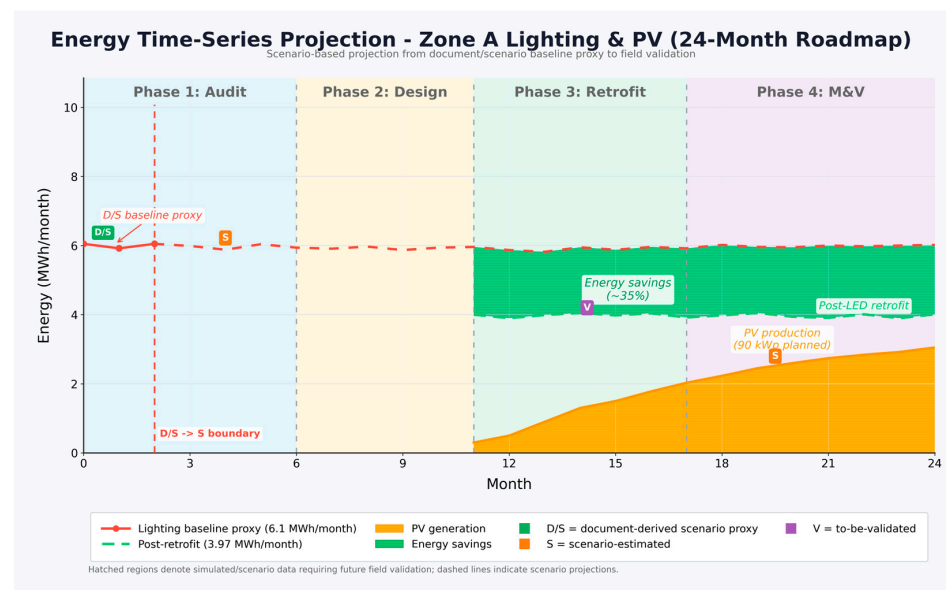


Figure 5. Energy time-series projection for Zone A lighting and PV over the 24-month roadmap. The initial value represents a document-derived/scenario baseline proxy (D/S), not a measured baseline; subsequent months present scenario-estimated (S) and to-be-validated (V) projections. The chart illustrates the lighting baseline proxy (6.1 MWh/month), the post-LED retrofit reduction scenario (approximately 35%), and the expected PV generation ramp-up (90 kWp planned). Hatched area denotes simulated data requiring future field validation. Dashed lines indicate scenario projections pending field validation.

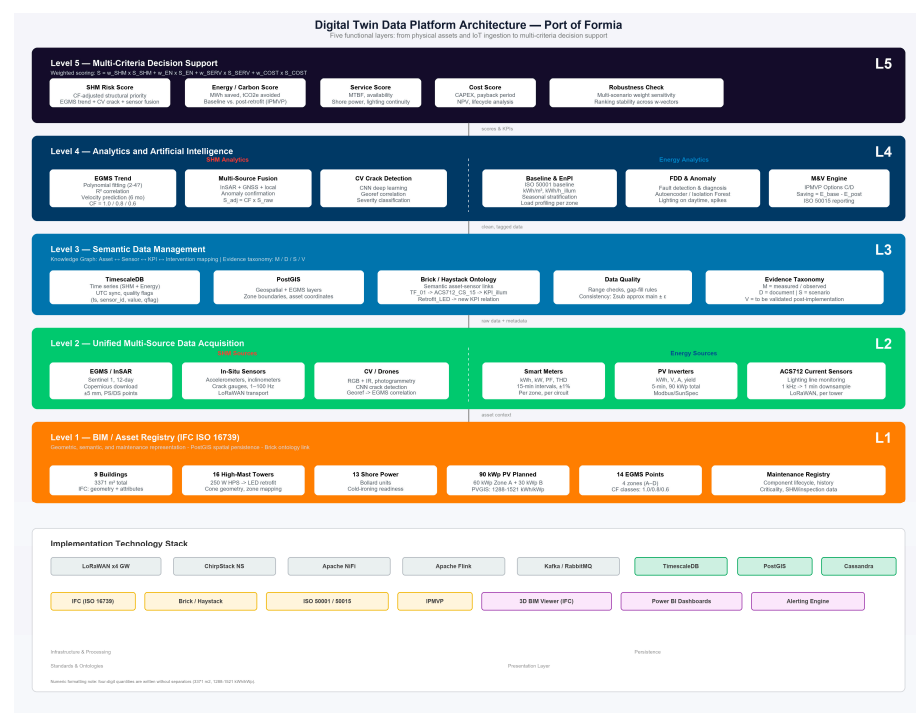


Figure 6. DT data platform architecture for the Port of Formia. Five functional layers span from BIM/Asset Registry (Level 1) through unified data acquisition (Level 2), semantic data management with Brick/Haystack ontology (Level 3), dual SHM and Energy analytics with AI (Level 4), to multi-criteria decision support (Level 5). The implementation technology stack details infrastructure components, persistence engines, standards, and presentation interfaces. Arrows and colors distinguish the direction of data flow and the functional separation among the five layers.

As shown in Figure 7, the available case-study localization layer supports the georeferenced association of assets, EGMS points, lighting towers, electrical panels, shore-power bollards, and planned PV areas. Each asset can then be tagged with zone membership, measurement point IDs, and energy cluster classification, enabling automated KPI computation at both asset and zone level within the unified DT environment once the live data layer is commissioned.

To further address the need for case-study visual evidence, Figure 8 provides a dashboard-style synthesis of the Port of Formia DT implementation layer. The figure combines the sensor and asset planimetry with the quantitative values reported in the article, including the 90 kWp planned PV portfolio, the central PV generation estimate of 126.4 MWh/year, the lighting technical saving estimate of 34.1 MWh/year, the combined avoided-emission estimate of 37.7 tCO₂e/year, and the monitoring assets and validation criteria required by the roadmap.

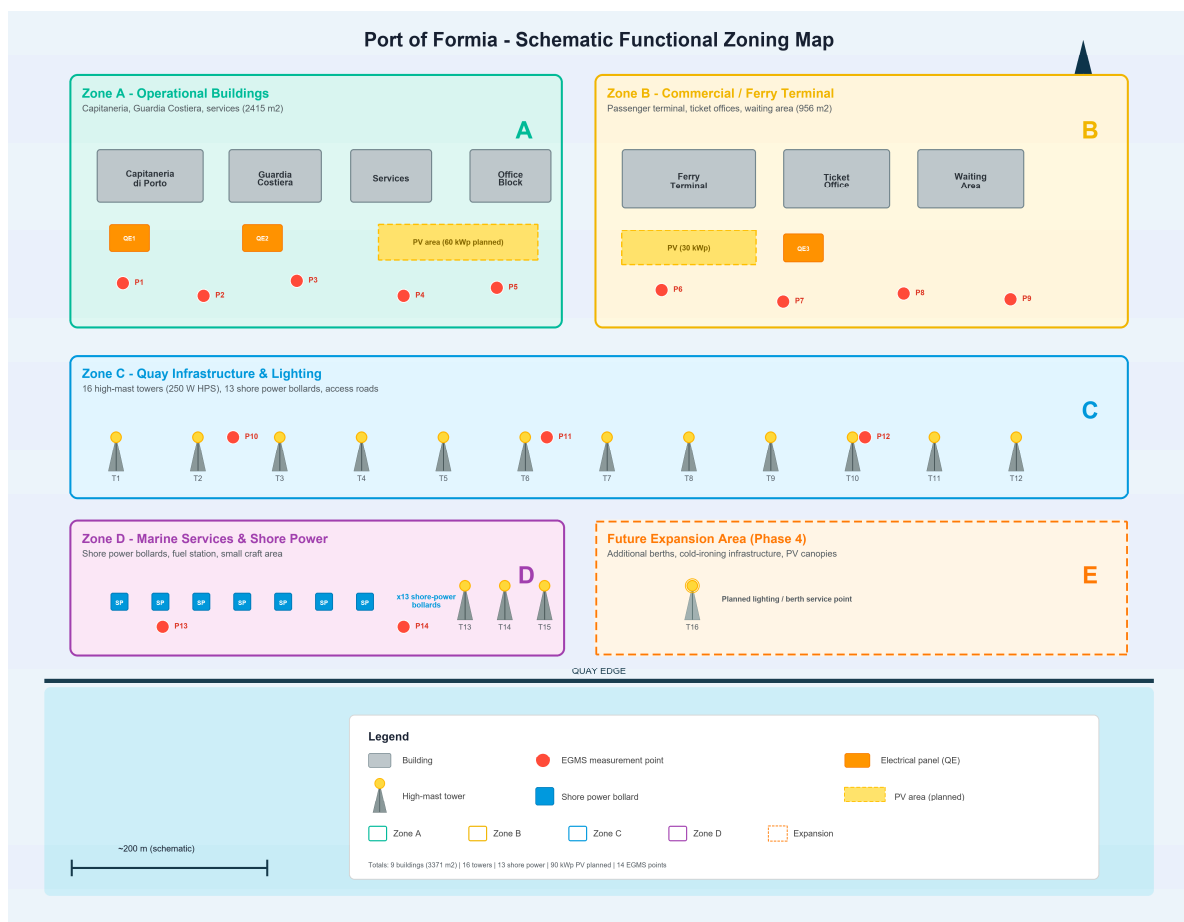


Figure 7. Case-study asset localization map used for the DT implementation layer. The map identifies functional zones, EGMS points, high-mast lighting towers, electrical panels, shore-power bollards, and planned PV areas; it replaces the previously mismatched BIM sight-cone caption.

3.7. Validation Roadmap and Acceptance Criteria

The following roadmap should not be read as a simple IT implementation plan, but as a protocol for progressive validation on three levels: (i) pre-operational feasibility assessment of interventions at the documentary and scenario-based level; (ii) acquisition of a robust annual baseline; (iii) post-intervention verification compliant with IPMVP (Table 13).

Table 13. Validation protocol outputs and acceptance criteria associated with the implementation roadmap.

Phase	Archivable Output	Risk Addressed	Acceptance Criterion	Data Produced
Phase 1 Metering setup	Commissioning dossier	Wrong boundary and timestamp drift	Uptime > 95%; main vs. sub-meter reconciliation within +/−5%	Validated meter map, communication logs, synchronization checks
Phase 2 Baseline acquisition	Baseline report	Weak or biased baseline	Data completeness ≥ 90%; documented outlier rules and frozen baseline window	12-month baseline dataset with contextual variables
Phase 3 Intervention deployment	As-built commissioning report	Design/as-built mismatch	Installed powers and equipment IDs consistent with design within +/−5%	As-built retrofit registry and updated BIM tags
Phase 4 Post-intervention M&V	Final annual M&V report	Overclaiming of energy or carbon benefits	IPMVP-compliant report with stated uncertainty and explained deviations	Verified savings and avoided-emission calculations

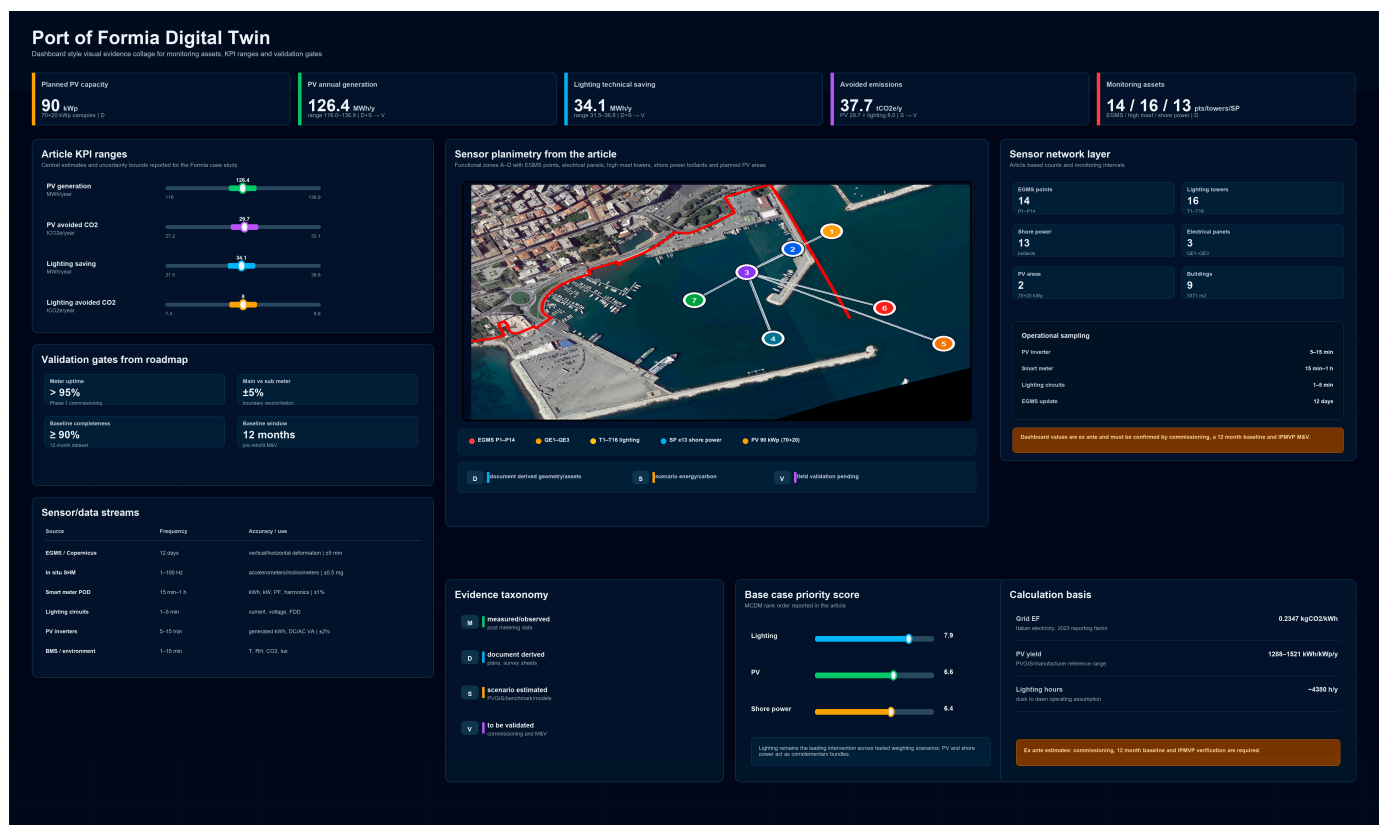


Figure 8. Dashboard-style visual evidence collage for the Port of Formia Digital Twin. The figure combines the case-study sensor/asset planimetry with article-based KPI ranges, monitoring-asset counts, operational sampling intervals, M/D/S/V evidence classes, prioritization scores, and validation gates. Values are document-derived and scenario-estimated, not final M&V outputs. Note: The dashboard is a mock-up intended to show how the proposed DT would organize available evidence and future live data. The reported values remain ex-ante estimates and must be confirmed through sensor commissioning, acquisition of a 12-month baseline, and IPMVP-compliant post-intervention M&V. Numbered KPI blocks and colors distinguish evidence categories, monitoring domains, and validation gates.

As detailed in Table 13, the protocol defines specific outputs and acceptance criteria for each phase of the implementation roadmap. This structured approach reduces the

epistemological risk typical of brownfield ports, where interventions are often already designed despite the absence of historical metering data.

The implementation roadmap for the Port of Formia is designed as a progressive validation protocol structured to mitigate the epistemological risks inherent in brownfield environments. The process is organized into four chronological phases that integrate physical infrastructure, semantic data management, and rigorous performance verification:

3.7.1. Phase 1: Metering Infrastructure Setup

The initial phase, spanning from month T0 to T + 3, is dedicated to establishing the sensing and communication layers. The architecture involves the strategic deployment of four LoRaWAN gateways across the port's functional zones, followed by rigorous radio coverage validation to ensure signal resilience. Concurrently, the metering infrastructure is enhanced by integrating smart meters at the primary Points of Delivery (PODs), lighting control panels, and shore power bollards, while photovoltaic string inverters are interfaced via the Modbus protocol. At a granular level, ACS712 current sensors are deployed on lighting circuits, with the provision for integrating environmental probes within port buildings.

This raw data stream is subsequently ingested by the ChirpStack network server and normalized within the data platform to ensure persistence in a TimescaleDB database. Time synchronization across all nodes is maintained via the NTP, a critical requirement for subsequent multi-domain analytics.

3.7.2. Phase 2: Baseline Acquisition

From month T + 3 to T + 15, the focus shifts to the acquisition of a robust reference dataset. Regarding the energy domain, a 12-month continuous monitoring campaign is conducted to define the Energy Baseline (EnB), accounting for contextual variables and identifying statistical outliers. Simultaneously, the DT integrates SHM components by processing EGMS satellite data.

This workflow utilizes zone-based screening and interpolation procedures to evaluate long-term deformation trends and displacement velocities at critical points. At the conclusion of this period, a comprehensive technical report is produced to freeze the energy and structural baselines, providing the necessary comparative foundation for subsequent phases and ensuring data quality in compliance with the ISO 50015 standard.

3.7.3. Phase 3: Intervention Deployment

The execution phase (T + 12 to T + 18 months) encompasses the implementation of energy efficiency measures and their concurrent integration into the BIM environment. The core of the intervention includes the installation of a distributed photovoltaic system, consisting of a 70 kWp array in the parking area and a 20 kWp system at the bus terminal. In parallel, the lighting infrastructure undergoes a comprehensive upgrade via the LED retrofit of 12 existing towers and the addition of four new high-mast units to optimize illuminance levels.

Each new asset is recorded in the as-built registry and assigned unique BIM tags, linking the physical entity to its respective real-time data feed—including measurement devices installed on service bollards to monitor shore power consumption and service continuity.

3.7.4. Phase 4: Post-Intervention Validation and M&V

The final phase (T + 18 to T + 30 months) is dedicated to ex-post validation and the quantification of benefits. Adhering to the IPMVP Option C (Whole Facility) guidelines, a post-intervention dataset of at least 12 months is acquired to normalize for seasonal

variations. Energy savings are calculated using regression models based on independent variables, enabling the quantification of avoided CO₂ emissions using updated national emission factors. The evaluation is completed by a detailed economic appraisal (NPV, IRR, and Payback Period) to validate the financial sustainability of the project.

The success of the interventions is measured against ex-ante acceptance criteria: for the PV systems, actual production is compared against the estimated range of 116.0–136.9 MWh/year; for the lighting system, technical savings on the replaced fleet are distinguished from any load increases associated with new service requirements. Deviations exceeding ± 15 –20% trigger formal review protocols regarding system boundaries or data quality, ensuring maximum transparency in the final reporting.

4. Discussion

4.1. Positioning of the Pre-Operational Feasibility Assessment Approach

The main contribution is the construction of a progressive validation pipeline applicable to brownfield port contexts without historical metering. The paradigm of progressive initialization is reflected in the pre-operational results: EGMS analysis provides initial screening evidence on the deformation state of port buildings and shared energy services; bounded ex-ante estimates quantify expected benefits without overclaiming unverified savings; and the data-platform design demonstrates the architectural feasibility of applying the proposed workflow to the real case study.

The work should not be interpreted as a purely conceptual framework. While not yet presenting twelve months of post-retrofit measurements, the manuscript offers a pre-operational technical feasibility assessment with quantitative estimates—with PV production ranges (116–137 MWh/year), lighting savings (31.5–36.8 MWh/year), avoided emissions (27–32 tCO₂e/year for PV, 7–9 tCO₂e/year for LED retrofit)—and a validation roadmap with explicit acceptance criteria (Section 3.7, Table 13). This positioning is consistent with advanced studies of DTs for building energy management, in which pre/post intervention scenario comparison is designed in the design phase and not only verified retrospectively [27–36].

The comparative positioning introduced in Table 2 clarifies the novelty: the present work does not propose yet another energy-focused DT, but, to the authors' knowledge, one of the first pre-operational frameworks to integrate EGMS/InSAR-based structural screening, a planned in situ and computer-vision validation layer, ISO 50001/50015 and IPMVP-oriented smart metering, and hybrid multi-criteria prioritization within a single pipeline for the port built environment. The pre-operational feasibility assessment (Section 3.6), supported by the five-level data platform and georeferenced asset model, demonstrates architectural coherence and deployment readiness, not yet a live synchronized DT.

4.2. Interpretation of Empirical Results and Ex Ante Estimates

The EGMS analysis presented in Section 3.1 shows a second-degree polynomial fit with $R^2 = 0.7432$ for Zone A. The moderate value confirms that satellite-derived data alone provide indicative rather than definitive assessments of structural condition, consistent with the confidence class framework adopted in Section 2.3.2. This result justifies the methodological choice to integrate EGMS with in situ sensors and computer vision surveys to achieve higher confidence levels in subsequent phases of the roadmap.

The robustness check summarized in Table 11 indicates that the lighting retrofit remains the leading priority intervention across all tested weighting scenarios. This is significant: it confirms that this ranking does not depend on a single expert-based weight set but is robust with respect to variations in decision preference toward structural, energy, service, or cost criteria. The second and third positions (PV and shore power) vary

depending on the scenario, suggesting that these interventions should be considered as complementary bundles rather than mutually exclusive alternatives.

The confidence class approach mitigates the risk of overclaiming: for the Formia case, the manuscript integrates documentary evidence (D) and scenario-based estimates (S), maintaining explicit distinction from post-implementation validated results (V). The scenario envelope (Table 10) quantifies this transparency: each estimate is reported with a range (low/high case) and principal drivers of uncertainty, avoiding point estimates that would suggest false precision for a system not yet metered.

The quantitative findings reinforce this interpretation. The lighting retrofit bundle shows an installed power reduction of 7.2–8.4 kW across the retrofitted asset base, equivalent to 31.5–36.8 MWh/year of gross technical energy savings (approximately 4380 operating hours per year dusk-to-dawn). The 90 kWp PV portfolio corresponds to 116–137 MWh/year of expected generation, with avoided emissions of 27.2–32.1 tCO₂e/year (ISPRA 2023 factor). These values are presented not as verified savings but as bounded engineering estimates that the validation roadmap is designed to confirm, revise, or reject.

4.3. Limitations and Mitigation Strategies

The findings of this study define a technical and architectural baseline for a port-centric DT, though their current evaluative status is characterized by specific boundary conditions. Regarding the SHM data, while the EGMS provides millimetric precision, its 12-day temporal resolution is optimized for identifying long-term, slow-moving trends. To address rapid phenomena such as subsidence jumps or mechanical impacts, the framework (Section 2.3.3) provides for the future integration of in situ accelerometers and computer vision surveys, a task scheduled for Phase 2 of the roadmap. Furthermore, the statistical fitting of this data involves inherent constraints; for example, the use of five measurement points in Zone A results in limited degrees of freedom ($df = 2$ for a second-degree polynomial). Consequently, the obtained $R^2 = 0.74$ result serves as a spatial screening indicator rather than a conclusive statistical model. The parabolic functional form was selected for its parsimony, as it effectively captures non-linear subsidence gradients without overfitting the currently sparse dataset.

A significant factor in the pre-operational assessment is the absence of a measured energy baseline. Given the lack of historical metering, ex ante estimates are derived from documented intervention scales and peer-reviewed benchmarks (e.g., PVGIS), a condition known to contribute to performance-gap risks in non-domestic facilities where occupancy drivers are not yet fully observed [74,75]. The roadmap (Section 3.7) mitigates this by mandating the acquisition of a robust 12-month baseline during Phase 2 ($T + 3$ to $T + 15$ months) as a prerequisite for IPMVP-compliant verification. This process is governed by specific acceptance criteria (Table 13) to ensure data reliability. Additionally, the correlation between energy consumption and contextual variables—such as heating/cooling degree-days, vessel traffic, and passenger volumes—will be quantifiable only once the metering infrastructure becomes fully operational, as these parameters have not been archived historically. Furthermore, the generalizability of the case study is currently focused on a Category II Mediterranean port; extending this framework to industrial ports or different climatic zones will require further cross-validation. From a cybersecurity perspective, while baseline recommendations are established in Section 2.2.2, full-scale compliance with frameworks such as IEC 62443 remains a future implementation goal. These factors clarify the current status of the research as a demonstration of technical feasibility and architectural coherence. Full validation of the energy-aware DT for existing port infrastructure will be achieved upon completion of the four-phase roadmap and the subsequent publication of verified M&V results.

The generalizable elements of the framework are the five-layer architecture, the M/D/S/V evidence taxonomy, the ISO/IPMVP-aligned M&V logic, the confidence-adjusted SHM gate, and the multi-criteria prioritization workflow. The local elements are the Mediterranean solar resource, Italian electricity-emission factors and regulatory references, the Category II port layout, the specific mix of lighting/PV/shore-power assets, and the density of EGMS measurement points available around Formia.

4.4. Comparison with Existing Literature

The results of the present work can be positioned relative to the four key studies identified in the comparative positioning (Table 2). Compared with the review by do Amaral et al. [17], which maps energy DT applications without addressing the port context or SHM integration, the present framework adds two elements absent from the reviewed literature: (i) structural screening as an explicit gate for energy prioritization, and (ii) the M/D/S/V taxonomy that renders transparent the epistemological status of each result. Relative to the port case study by Sifakis et al. [36], which quantifies savings from LED and PV retrofit in Greek ports but excludes structural monitoring and explicit M&V governance, the present study is more conservative in its estimates (not claiming verified savings in the absence of metering) but more comprehensive in its validation pipeline.

The framework by Agostinelli et al. [27] proposes a DT for smart buildings with predictive analytics but operates on single buildings in the operational phase with measured data already available: the principal difference lies in the pre-operational paradigm adopted here, which addresses the specific challenge of brownfield ports lacking historical records. Finally, compared with the intelligent port lighting case by Agostinelli et al. [28], which focuses on adaptive dusk-to-dawn control, the present work extends scope to the entire port district (buildings, PV, shore power, lighting) and introduces the structural dimension as a prerequisite for retrofit decisions. Overall, the framework's novelty lies not in the individual components (each present in at least one cited reference) but in their integration within a single pre-operational feasibility assessment workflow with explicit methodological transparency.

5. Conclusions

5.1. Synthesis of Results

The principal finding of this work is the demonstration of technical and architectural feasibility for characterizing a brownfield port lacking historical metering before IoT infrastructure commissioning, provided that structural screening and energy governance are treated as coupled systems within a single pre-operational DT pipeline. Applied to the Port of Formia (9 buildings, 3371 m², 16 lighthouse towers, 90 kWp PV, 13 shore power charging stations), the five-level framework has produced: a multi-zone EGMS screening analysis with differentiated confidence classes ($R^2 = 0.74$ for Zone A, CF = 0.6–1.0), bounded ex-ante estimates for PV (116–137 MWh/year) and lighting (31.5–36.8 MWh/year), and a preliminary multi-criteria intervention ranking robust across five weighting scenarios. Each result is classified according to the M/D/S/V taxonomy, rendering explicit the status of the evidence and the pathway toward post-implementation validation. The main results are:

- Technical feasibility assessment: the architecture is coherent with open standards (IFC, Brick/Haystack, ISO 50001/50015, IPMVP) and with established technologies (LoRaWAN, ChirpStack, Apache NiFi/Flink, TimescaleDB). Section 3.6 demonstrates that the data platform architecture and BIM/asset model schema have been designed for deployment on the real case study, with 9 buildings inventoried (3371 m²),

16 lighthouse towers, 13 shore power charging stations, and 90 kWp of planned PV; it does not yet claim live synchronization or verified operational performance.

- SHM-Energy integration: the framework currently combines EGMS/InSAR screening with a planned in situ sensor and computer-vision validation layer, and links this SHM logic to smart metering and sub-metering aligned with ISO 50001. The EGMS analysis (Section 3.1) has produced deformation screening for the four port zones, with confidence classes that condition, rather than conclusively determine, the hybrid prioritization model.
- Transparent KPIs and scenario envelopes: a multi-domain KPI set has been defined (structural, energy, carbon, operational) that can be calculated progressively as metering produces data. Ex-ante estimates (Section 3.3) are reported as bounded ranges—116–137 MWh/year for PV, 31.5–36.8 MWh/year for lighting retrofit—with drivers of uncertainty made explicit (Table 10); carbon values are treated as gross-displacement upper bounds until self-consumption, exports, and post-retrofit loads are measured.
- Robust hybrid prioritization: the multi-criteria scoring (Section 3.4) identifies lighting retrofit as the leading priority intervention across all tested weighting scenarios (Table 11), confirming the robustness of this result relative to variations in decision preferences.
- Validation roadmap with M&V criteria: Section 3.7 defines a four-phase protocol (metering setup, baseline acquisition, intervention deployment, M&V verification) with quantitative acceptance criteria (Table 13) that enable acceptance, revision, or rejection of ex ante estimates once post-implementation data become available.

5.2. Recommendations for Port Authorities and Asset Managers

To maximize the benefits of a port DT, the following strategic and operational recommendations are proposed:

- Invest in smart metering as a prerequisite: Without structured metering compliant with ISO 50001 and IPMVP, even the most advanced DT remains primarily descriptive. Metering should be prioritized at locations of highest energy impact—lighting circuits, charging stations, and PV inverters—within the first three months, consistent with staged renovation and public-building efficiency practices [76,77].
- Adopt open semantic frameworks (Brick/Haystack): Open ontologies facilitate application portability across ports and reduce the costs of future integration. Using IFC for the BIM model ensures interoperability with mainstream facility management software.
- Integrate SHM and energy: Structural monitoring and energy management should not be treated as separate silos. The port DT must unify prioritization in order to maximize the joint benefits of structural safety and energy efficiency.
- Commit to disciplined M&V: All measurement metrics, boundaries, baselines, and evaluation durations (at least 12 months pre- and 12 months post-retrofit for significant interventions) should be defined before deployment. Acceptance criteria must be established in advance to avoid post hoc interpretations.
- Ensure data governance and cybersecurity: Clearly define responsibilities for data quality, synchronization, access, and security for operational technology (OT/ICS). Cyber risks in connected critical infrastructure should not be underestimated [78].

5.3. Future Research Directions

Looking forward, several avenues of research emerge to further enhance the integration of structural and energy monitoring within port DT. One promising direction involves the development of hybrid machine learning models capable of detecting anomalies across

both structural and energy systems. By integrating InSAR satellite measurements, in situ sensors, and energy metering data, predictive models could be designed to correlate structural degradation with energy performance. Such models would move beyond static thresholds, enabling proactive maintenance and energy optimization. Feature-selection techniques and susceptibility mapping from geospatial machine learning could be combined with thermal-storage-aware modules in conditioned port buildings to capture complex interactions between infrastructure behavior and energy demand [79,80]. Another important research direction concerns the extension of semantic ontologies for port assets. By expanding frameworks like Brick to capture functional dependencies, such as the impact of a degraded charging station on downstream services, DTs could support automated reasoning for predictive maintenance, operational decision-making, and service optimization. This semantic enrichment would allow DTs to not only monitor individual assets but also understand their interdependencies within the port ecosystem. Further work is needed to improve MCDM methods for prioritizing interventions. Applying techniques such as AHP or TOPSIS, combined with comprehensive sensitivity analyses, would allow stakeholders to evaluate the robustness of intervention rankings against variations in criterion weights, including inputs from diverse port authorities and operational teams. The concept of federated DTs also represents a promising frontier. Standardizing IFC and Brick schemas across ports could enable cross-port benchmarking, facilitate the transfer of best practices, and support collective learning from heterogeneous infrastructure contexts. The application of AI to predictive maintenance in lighting systems presents an immediate operational benefit. Deep learning models could analyze current patterns and harmonic distortion to anticipate LED or ballast failures, thereby reducing unscheduled maintenance, extending asset lifecycles, and optimizing energy efficiency.

Together, these research directions point toward a future in which port DTs may evolve from descriptive and diagnostic tools into predictive and prescriptive platforms capable of guiding maintenance, energy management, and strategic investment decisions after smart metering, field SHM confirmation, and long-term operational testing are completed.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AFIR	Alternative Fuels Infrastructure Regulation
BEMS	Building Energy Management System
BIM	Building Information Modeling

BMS	Building Management System
CAPEX	Capital Expenditures
DT	Digital Twin
EPBD	Energy Performance of Buildings Directive
EGMS	European Ground Motion Service
EnMS	Energy Management System
EnPI	Energy Performance Indicator
EUI	Energy Use Intensity
FDD	Fault Detection and Diagnostics
IFC	Industry Foundation Classes
InSAR	Interferometric Synthetic Aperture Radar
IPMVP	International Performance Measurement and Verification Protocol
IoT	Internet of Things
KPI	Key Performance Indicator
M&V	Measurement and Verification
MCDM	Multi-Criteria Decision Making
MP	Measurement Point (EGMS)
MTBF	Mean Time Between Failures
MTTP	Mean Time To Repair
NTP	Network Time Protocol
O&M	Operation and Maintenance
OPEX	Operational Expenditures
OT	Operational Technology
PV	Photovoltaic/Photovoltaics
SHM	Structural Health Monitoring
THD	Total Harmonic Distortion
UPS	Uninterruptible Power Supply

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